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**Earnings Dynamics and Profile Heterogeneity:
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Earnings Dynamics and Profile Heterogeneity: Estimates from Japanese Panel Data ^{*}

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Abstract

The recent empirical work on earnings processes by Guvenen (2009) using US panel data finds that ignoring heterogeneity in earnings profiles among individuals leads to an upward bias in the autoregressive parameter of earnings shocks. It then argues that the existing assumptions in incomplete markets, heterogeneous-agent models, almost all of which require highly persistent earnings shocks and no individual- and group-specific differences in earnings growth rates, may be inappropriate. This paper investigates the applicability of this US data-based debate to other developed countries by using a panel of Japanese male earnings. The results indicate that it is possible to corroborate Guvenen's arguments, despite some differences in the estimates.

Keywords: Labor earnings risk, Heterogeneous earnings profiles, Incomplete markets models, Transitory shock, Persistent shock.

JEL Classification: C33, D31.

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1 Introduction

The modeling of an individual's earnings dynamics is a longstanding issue that has been debated over three decades in the field of labor economics, and it is more recently becoming an essential element of quantitative macroeconomic studies under incomplete markets environments.¹

Among such recent studies on earnings dynamics, the most interesting and suggestive one from the viewpoint of macroeconomics is probably Guvenen (2009). His findings, which are based on a US panel drawn from the Panel Study of Income Dynamics (PSID), are in sharp contrast to the assumptions about earnings processes in the existing incomplete markets, heterogeneous-agent models (especially with a life-cycle dimension), almost all of which require that idiosyncratic earnings shocks be highly persistent; in other words, that the autoregressive parameter be near or exactly equal to one.² A succinct justification for this highly persistent-shock assumption is that some earlier papers (e.g., MaCurdy (1982), Abowd and Card (1989), Moffitt and Gottschalk (1995)) provide evidence in favor of the unit root model or its more flexible versions.³ Another one is, to borrow Lucas' (2003, p.10) phrase, consistency with "the fanning out over time of the earnings and consumption distributions within a cohort" that Deaton and Paxson (1994)

¹ See, e.g., Heathcote et al. (2009) and Meghir and Pistaferri (2010) for recent surveys from this perspective.

² In this paper, we focus entirely on models with an exogenous and relatively simple univariate earnings process (specified as an AR(1) shock plus a transitory shock) to satisfy the objective of this paper described in the next two paragraphs. However, previous studies have attempted to specify the conditional variance of shocks, endogenize earnings dynamics, and incorporate multivariate processes or more flexible processes with many types of heterogeneity. See, e.g., Meghir and Pistaferri (2004), Huggett et al. (2006), Altonji et al. (2009), and Browning et al. (2009) for these extensions.

³ More recent studies (e.g., Blundell et al. (2008) and Attanasio et al. (2008)) still refer to the findings by MaCurdy (1982) and Abowd and Card (1989) as justification when assuming the unit root model of earnings shocks, despite subsequent contributions that report evidence in favor of moderate earnings shocks (e.g., Baker (1997) and Haider (2001)). Thus, this evidence in favor of the unit root model still has a great influence on the literature. In light of these subsequent studies, Moffitt and Gottschalk (2002, 2009) extend their original sample period up to 1996 or 2004 and report new estimation results to confirm their previous findings.

found.⁴

What makes Guvenen's work interesting is not only that it documents that the observed fanning-out effect can be explained even under moderate earnings shocks, but also that it includes the new findings that ignoring heterogeneity in earnings profiles (i) leads to an upward bias in the autoregressive parameter (consequently, a near unit-root model) and (ii) obscures a significant difference in the dispersion of earnings growth rates between college-educated and high-school-educated groups. The former finding explains why earlier studies such as MaCurdy (1982) and Abowd and Card (1989) support the unit root model of earnings processes, invalidating the first justification for highly persistent shocks if it is robust.⁵ The latter finding, on the other hand, explains why earlier studies such as Hubbard et al. (1994, 1995) and Carroll and Samwick (1997) obtain similar estimation results for earnings processes among groups with different educational backgrounds, contrary to predictions from human capital investment theory.⁶ Thus, Guvenen's findings force us to reconsider the modeling strategy of earnings processes that we wish to use as an input in constructing incomplete markets, heterogeneous-agent models.

In this paper, we focus on the above-mentioned two points, (i) and (ii), and ask whether they are PSID data-specific by studying a panel of Japanese individuals, partly because there is a possibility that different conclusions may arise from the analysis of other panels, and partly because of the first step of evaluating whether the US debate (and consequently, theory tailored for the US data) is universally applicable to other developed countries. The data used in this

⁴ For further analysis and discussions relating to this result, see, e.g., Storesletten et al. (2001, 2004a,b).

⁵ More recently, Hryshko (2009) reexamines the model with a dispersion of earnings growth rates and finds little evidence in favor of profile heterogeneity using the PSID data. Therefore, this finding is not necessarily conclusive, which also motivates the present paper. Beyond this controversy on earnings dynamics, a new literature has begun to take an approach that distinguishes the model allowing for profile heterogeneity from the unit root model in a more structural way. See, e.g., Guvenen and Smith (2009).

⁶ See, e.g., Becker (1993), and a more recent paper, Guvenen and Kuruscu (2010), for a comprehensive discussion about the relationship between human capital investment and earnings (or wage) profiles.

paper are drawn from the Japanese Panel Survey of Consumers for the period 1993–2004. From this survey, it is possible to create panel data sets of earnings and relevant variables for individuals and by education group, as does previous empirical work based on the PSID. We consider both balanced and unbalanced panels, mainly because we examine the robustness of our results under the sample selection criteria used in this paper, and because there exists no corresponding previous work for Japan.⁷ Consequently, we include in our analysis a specification of earnings processes similar to that of Baker (1997) and Haider (2001) as well as Guvenen’s (2009) specification.

The use of Japanese data is of particular interest for the purpose of this study, not only because we can analyze earnings dynamics for individuals and by education group in a similar way to the US studies, but also because Japan has been recognized as representative of countries with relatively low income inequality compared with the United States or as a country with different earnings profiles from the United States. Indeed, as Moriguchi and Saez (2008, Section II) point out, there is a general belief that income inequality is much smaller in Japan than in the United States (see Tachibanaki (2005, 2006) and Ohtake (2005) for this debate). On the other hand, the question of how and why earnings profiles for Japan are different from those for the United States has attracted the interest of many researchers in the context of estimation of Mincer-type earnings (or wage) regressions using cross-sectional data (see, e.g., Hashimoto and Raisian (1985, 1992), Mincer and Higuchi (1988), Clark and Ogawa (1992a,b), and Abe (2000)).

⁷ There are a few papers that have studied consumption and income inequality using *cross-section* data of Japanese households from the National Survey of Family Income and Expenditure conducted by the Japanese government. For example, on the basis of this cross-sectional data, Ohtake and Saito (1998) analyze consumption inequality within a fixed cohort, following Deaton and Paxson’s (1994) method, and Abe and Yamada (2009) estimate an income process of Japanese households, using a similar specification to that of Storesletten et al. (2004b). The only study comparable to ours is Abe and Inakura (2007), who apply Abowd and Card’s (1989) method to a Japanese panel drawn from the same survey as ours, but they also do not focus on heterogeneity in earnings profiles.

Nevertheless, nobody has attempted to estimate earnings dynamics, as we do in this paper.

We obtain both corroborating evidence and some different findings. First, an increase in the variance of the earnings residual (defined as the deviation from a component of log real earnings common to all individuals) over time can also be observed in our data on Japanese individuals, and when we try to explain this increase using the models, ignoring profile heterogeneity (especially, the dispersion of earnings growth rates) leads to a substantial upward bias in the persistence of earnings shocks. Second, according to our estimation results by education group based on the unbalanced panel data, we cannot find a significant difference in the dispersion of earnings growth rates between the college-educated and the noncollege-educated groups. Third, the fixed effect (i.e., differences in the initial conditions at the time when individuals enter into labor markets) also has a significant effect on the variance of the earnings residual even in the model allowing for heterogeneous earnings profiles (hereafter called the profile heterogeneity model).⁸ Although the second and third findings are different from Guvenen’s findings for the United States, we do find evidence supporting his finding of a moderate earnings shock and a significant dispersion of earnings growth rates for each group. We also find that the estimates of the dispersion parameter of earnings growth rates are similar to those reported in Guvenen (2009), Baker (1997), and Haider (2001).

To provide additional evidence on causes of the preceding second result, we examine whether the result is sensitive to aggregation across diverse groups, and we also attempt estimation that allows for the possibility of occupational differences in earnings profiles (pointed out by, e.g.,

⁸ In this paper, we use the term “profile heterogeneity model” as in Baker (1997). We shall not use the term “heterogeneous income profile model” as in Guvenen (2009) and Hryshko (2009) because we focus on earnings and because income is usually used in a broader sense than earnings. See, e.g., Ehrenberg and Smith (2009, pp.34–35) for the relationship between earnings and income. For the same reason, we use the simple term “restricted model” instead of “restricted income profile model” later on.

Topel (1991)).⁹ We show that both aggregation and occupational differences can account for part of the dispersion in earnings growth rates, so that the estimate of the dispersion parameter can have a slightly upward bias. We show that the second result holds as long as our data set is used, but the profile heterogeneity model still cannot be rejected. We argue that our findings as a whole indicate the importance of allowing for heterogeneity in earnings growth rates in modeling earnings dynamics, which agrees with the main message drawn from Guvenen’s findings for the United States, despite some differences in the details of the estimates.

The paper is organized as follows. In Section 2, we first summarize the findings and arguments by Guvenen on which we focus in this paper, for the sake of completeness. We then describe, in Section 3, the Japanese panel data and show the characteristics of the samples derived from the data. In Section 4, we present some corroborating evidence and new findings using the Japanese panel data. Section 5 concludes.

2 The Profile Heterogeneity Model

The hypothesis that we concentrate on in this paper is very simple: initial earnings and earnings growth rates vary across individuals, so that each individual has a specific earnings profile over their life cycle. Despite various attempts since Lillard and Willis (1978), this hypothesis has remained at the heart of empirical work on earnings dynamics in the labor economics literature (see, e.g., Baker (1997), Haider (2001), Baker and Solon (2003), and references therein), but it has not explicitly been connected with recent work in modern quantitative macroeconomics, until Guvenen (2007, 2009).

The specification of the earnings process used by Guvenen is standard in the literature on labor economics rather than macroeconomics, which is composed of three components: a

⁹ Carroll and Samwick (1997) estimate the unit root model of earnings processes with no profile heterogeneity not only by education group but also by occupation group. Guvenen (2009) focuses on their estimation results by education group and argues point (ii) mentioned above.

common factor across all individuals, individual-specific factors, and stochastic shocks. More precisely, it is given by:

$$\begin{aligned} y_{it} &= f(X_{it}, \psi_t) + (\alpha_i + \beta_i X_{it}) + z_{it} + \epsilon_{it}, \\ z_{it} &= \rho z_{it-1} + \eta_{it}, \quad z_{i0} = 0, \end{aligned} \tag{1}$$

where y_{it} is the natural logarithm of real earnings of individual i in year t , and X_{it} is a measure of individual i 's labor market experience in year t .¹⁰ The first term on the right-hand side of the first equation captures the variation that is common to all individuals (called the mean earnings profile or common life-cycle component in the literature), and $f(\cdot)$ is assumed to be a polynomial function of X_{it} with a parameter vector ψ_t . The second term $(\alpha_i + \beta_i X_{it})$ captures individual-specific factors, in which α_i and β_i allow individuals to have different initial earnings and earnings growth rates, relative to the mean earnings profile. Transitory shocks, ϵ_{it} and η_{it} , are independent of each other and over time, with zero mean and variances σ_ϵ^2 and σ_η^2 .¹¹ Individual-specific parameters α_i and β_i are assumed to be independent of the transitory shocks ϵ_{it} and η_{it} , and have zero mean, variances σ_α^2 and σ_β^2 , and a covariance $\sigma_{\alpha\beta}$.

To focus on the last two factors, define the earnings residual as $\hat{y}_{it} \equiv y_{it} - f(X_{it}, \psi_t)$.

¹⁰ In the literature, there are subtle variations in the definition of the subscript t . One definition is the year as is the case here, which is adopted by, e.g., MaCurdy (1982), Abowd and Card (1989), Baker (1997), and Haider (2001). Guvenen (2009) further distinguishes notation between the year and the number of years of labor market experience. A second definition is age, which is adopted by, e.g., Moffitt and Gottschalk (1995, 2002, 2009), Storesletten et al. (2004a), and Guvenen (2007). All of these studies are based on the US PSID. However, if a very rich data set is available, as in the Canadian case of Baker and Solon (2003), then it would be ideal to follow their paper and define y_{it} as the log real earnings in year t of individual i born in year b . In other words, the definition of the subscript t (and consequently y_{it}) depends on the richness of data used in the analysis. As described in Section 3, our data sets are rather close to those of the previous studies using the year t definition, cited above, in terms of sample sizes and lengths of time periods. For this reason, here we define subscript t as the year. In our empirical analysis, however, we allow for differences in earnings variances among cohorts by considering three types of data sets.

¹¹ It is possible to allow these variances to vary with time. For simplicity of discussion, here we do not consider time-varying variances, but we deal with one such case in our empirical analysis.

Specification (1) then becomes:

$$\hat{y}_{it} = \alpha_i + \beta_i X_{it} + z_{it} + \epsilon_{it}. \quad (2)$$

One difference from a typical specification in the labor economics literature (e.g., Baker (1997) and Haider (2001)) is that equation (2) includes the transitory shock ϵ_{it} , which can be regarded as one characteristic of Guvenen's specification.¹² In contrast to this, a typical specification used widely in the macroeconomics literature (see, e.g., Storesletten et al. (2004a,b)) is given by:

$$\hat{y}_{it} = \alpha_i + z_{it} + \epsilon_{it}. \quad (3)$$

By comparison with (2), this specification can be interpreted as excluding, by assumption, the possibility of heterogeneity in earnings growth rates. The following is a short list of the main discussions and findings (on which we concentrate in this paper) associated with these two specifications:¹³

- The variance of \hat{y}_{it} under the restricted specification (3) is calculated as:

$$\begin{aligned} \text{Var}(\hat{y}_{it}) &= \sigma_\alpha^2 + \sigma_\epsilon^2 + \sigma_\eta^2 \sum_{j=0}^{t-1} \rho^{2j} \quad \text{if } \rho \neq 1, \\ &= \sigma_\alpha^2 + \sigma_\epsilon^2 + t\sigma_\eta^2 \quad \text{if } \rho = 1. \end{aligned} \quad (4)$$

Therefore, a highly persistent shock is the only factor that leads to a rise in the variance of log earnings. The restricted specification with $\rho \approx 1$ is consistent with Deaton and

¹² If the transitory component ϵ_{it} is interpreted as capturing measurement error, then ignoring it may lead to a downward bias in the persistence parameter ρ . In fact, a comparison between his findings and Baker's suggests that this possibility may be true for the US data-based analysis. Thus, this modification is important, although it may appear minor at first glance.

¹³ As mentioned previously, this section does not intend to provide a comprehensive survey of recent contributions. For such surveys from a macroeconomic perspective, see Heathcote et al. (2009) and Meghir and Pistaferri (2010). In particular, Section 3.1.5 and Table 2 of Meghir and Pistaferri (2010) summarize the main results in the extensive literature tersely.

Paxson's (1994) finding, a significant rise in the variance of log earnings within a cohort over the life cycle, which has been one reason for its acceptance in the macroeconomics literature (see, e.g., Storesletten et al. (2004a)).

- The unrestricted specification (2), which we call the profile heterogeneity model, is consistent with some compelling hypotheses based on the theory of human capital investment, such as heterogeneity in growth rates of earnings dependent on individuals' ability differences,¹⁴ while the restricted specification with $\rho \approx 1$ is not so, and its theoretical interpretation is not necessarily clear. In this respect, the restricted specification with $\rho \approx 1$ has not been preferred in the labor economics literature, even though it was not rejected (see, e.g., Baker (1997) and Haider (2001) for discussions).
- In a discussion that bridges these different views, Guvenen (2007, 2009) argues that it is possible to explain a rise in the variance of log earnings even under the unrestricted specification (2). The variance of \hat{y}_{it} calculated from (2) is:

$$\text{Var}(\hat{y}_{it}) = \sigma_\alpha^2 + \sigma_\epsilon^2 + \sigma_\eta^2 \sum_{j=0}^{t-1} \rho^{2j} + (2\sigma_{\alpha\beta}X_{it} + \sigma_\beta^2 X_{it}^2) \quad \text{if } \rho \neq 1. \quad (5)$$

This equation implies that, even if there are no highly persistent shocks (i.e., ρ is not close to one), differences in labor market experiences that will be accumulated as individuals get older, which appear as the last two terms, can lead to a rise in the variance of log earnings. Guvenen (2009) also notes that estimation of the earnings process (especially focused on the autoregressive parameter ρ) in the context of the unrestricted specification (2) with the transitory shock ϵ_{it} has *not* been done so far. According to his empirical work based on a US panel of earnings drawn from the PSID data, the unrestricted specification (2) is estimated to yield a moderate persistence (about $\rho = 0.8$) and a significant heterogeneity in earnings growth rates (i.e., $\sigma_\beta^2 > 0$) (see Table 1 of Guvenen (2009)). Given these

¹⁴ For a list of other theoretical justifications, see, e.g., footnote 7 of Haider (2001).

estimates, the last two terms can account for about 0.3 percent at age 30 and about 80 percent at age 65 (i.e., retirement age) of the variance $\text{Var}(\hat{y}_{it})$ (see Table 2 of Guvenen (2007)).

- Conversely, ignoring profile heterogeneity (i.e., assuming the restricted specification (3)) leads to an upward bias in the autoregressive parameter ρ . In the US case, for example, the estimate of ρ rises from 0.821 to 0.988 for all individuals (see Table 1 of Guvenen (2009)), which is close to the values that were extensively used in calibration studies that assumed the restricted specification (see, e.g., Huggett (1996) and Storesletten et al. (2004a)).
- Guvenen (2009) further notes that there exists *no* corresponding analysis that investigates the differences across education groups in the context of the unrestricted specification (2). His findings reveal that there are few differences in the estimate of ρ across education groups ($\rho = 0.805$ for the college-educated group and $\rho = 0.829$ for the high-school-educated group); however, the dispersion of the earnings profiles captured by σ_β^2 is significantly larger for the college-educated group, which is about 2.5 times as high as that of the high-school-educated group ($\sigma_\beta^2 = 0.00049$ for the college-educated group and $\sigma_\beta^2 = 0.00020$ for the high-school-educated group) (see Table 1 of Guvenen (2009)). This is inconsistent with studies such as Hubbard et al. (1994, 1995) and Carroll and Samwick (1997), which assume that there is no profile heterogeneity for all education groups (i.e., $\beta_i = 0$, and consequently, $\sigma_\beta^2 = \sigma_{\alpha\beta} = 0$).

Of the above-mentioned points, the empirical findings by Guvenen (2009) suggest that (i) we do not need to rely on the restricted specification assuming a highly persistent shock to develop incomplete markets, heterogeneous-agent models; and (ii) the assumption of no individual-specific or no education-group-specific differences in earnings growth rates may be inappropriate. Given this sharp contrast to the existing assumptions, corroborating his findings, and asking

whether they are PSID data-specific—in other words, asking whether the debate tailored for US data is universally applicable—is an important and necessary task, which also obviously affects the premise when one considers as the next step the microfoundations for earnings dynamics.¹⁵

In this paper, we use a panel of Japanese individuals, described in the next section, and as a starting point for this paper we first examine whether Guvenen’s (2009) new empirical findings for the United States summarized above hold up on the basis of that data, and thus for Japanese individuals.

3 The Data

3.1 The Japanese Panel Survey of Consumers

The data used in this paper are drawn from the Japanese Panel Survey of Consumers (hereafter JPSC) compiled by the Institute for Research on Household Economics (a public corporation duly approved by the Prime Minister and established in 1986 in cooperation with the Economic Planning Agency, currently the Cabinet Office of the Japanese government). The JPSC has been conducted in October every year since 1993, and it follows the same individuals, as does the PSID. Respondents to the survey are 1500 women in the age range 24–34 as of 1993. They were selected from the entire area of Japan on the basis of a two-stage stratified random sampling method.¹⁶ To administer the survey, survey conductors visit and distribute survey sheets to every household, and then collect them in person after one month. Questionnaire items in the JPSC include questions about, e.g., family composition changes, employment, consumption expenditure, income, savings, financial assets, loans, housing, consumer durables, time management, and satisfaction of life, some of which ask about not only the respondent but also her

¹⁵ See, e.g., Heathcote et al. (2009) for a survey of recent research on the microfoundations.

¹⁶ The 1995 Annual Report of the JPSC (Institute for Research on Household Economics (1995)) compares this sample with the results of other representative surveys including the census of Japan conducted in 1990, and concludes that the JPSC sample reflects the characteristics of the population quite well.

family members. Thus, adequate information about individuals and households is available from the JPSC, and it allows us to construct variables necessary for estimating the earnings processes of males, as in empirical work based on the PSID.¹⁷

In the JPSC, information about labor market experience is elicited by the following questions: “How long has your husband worked since his graduation from school? (Please respond in years and months.)” and “Does your husband currently work?” By combining these, it is possible to calculate the labor market experience of an individual with reasonable accuracy.¹⁸ The measure of labor earnings that we use in this paper is earnings before tax from employment and does not include labor portions of other types of income such as farm income, business income, market gardening income, and roomers and boarders income. Therefore, it is slightly narrow relative to the typical measure (total labor income) in previous studies using the PSID (e.g., Baker (1997), Haider (2001), and Guvenen (2009)); however, we do not attempt to reconcile this difference because there is no detailed information on the above items of income in the JPSC. Labor earnings in the year t survey refer to annual earnings in calendar year $t - 1$; therefore, to

¹⁷ A slightly inconvenient feature of the JPSC data, compared with the PSID data, is that the submission of an application form is required for use of the data, and after obtaining permission from the Institute the applicant receives a CD-ROM. The application form is downloadable from the Web site of the Institute for Research on Household Economics (<http://www.kakeiken.or.jp/en/>).

¹⁸ In the US literature, labor market experience is calculated from information on education using formulas such as $(\text{age} - \text{education} - 6)$ and $(\text{age} - \max(\text{years of schooling}, 12) - 6)$. In the JPSC, there is no question that asks years of schooling directly. Instead, the respondent provides information on her own and her husband’s educational background by selecting from various categories. It may be possible to calculate the labor market experience by inferring years of schooling from this answer in a similar way to the US literature. However, we did not adopt this method because of at least two difficulties. First, we cannot identify years of schooling for those who dropped out and repeated a grade. Second, it is difficult to pin down years of schooling for categories such as “both vocational school and high school” and “junior college or specialized vocational high school”. To deal with these, we need to make some assumptions about the relation between the educational background reported and years of schooling, but doing so may introduce measurement error. Although the use of retrospective questions also may introduce measurement error, it has the advantage that the calculation is simple and does not depend on additional assumptions.

convert nominal values into real ones, they are deflated by the consumer price index (using 2005 as the base year) in the corresponding calendar year. We follow convention in the literature and refer to the survey year as the observed year to avoid needless confusion. Appendix A contains details on our use of the data and the definitions of the variables used for analysis.

A common problem with panel data is that there is attrition for various reasons every year. The JPSC is no exception. In response to this problem, 500 women in the age range 24–27 as of 1997 have been added since 1997, and 836 women in the age range 24–29 as of 2003 have been added since 2003 as new respondents. In this paper, we use 12 waves covering the period from 1993 to 2004 (the latest survey available at the time of writing). Therefore, three samples (called in turn cohort A, cohort B, and cohort C by the Institute for Research on Household Economics) are available for that period; however, the last sample covered since 2003 (cohort C) is excluded from our analysis because of a scarcity of time periods.

Using 12 waves of the JPSC, we create three panel data sets. The first panel covers the survey years 1993–2004 and includes only the original JPSC sample (cohort A). This choice maximizes the number of years used for analysis but reduces the number of households considerably. The second panel covers the survey years 1997–2004 and includes both the original JPSC sample and the sample since 1997 (cohort A and cohort B). These two panels are balanced ones, so the second panel maximizes the number of households in the context of balanced panels. The third panel is, on the other hand, unbalanced and covers the survey years 1993–2004, which maximizes the number of households as well as the number of years. The samples used for analysis are selected from the raw data using the following criteria. (i) The respondent and her spouse are a continuously married couple. Further, the spouse (i.e., husband of the respondent) (ii) is classified as an employee using the definition of the JPSC (i.e., a wage or salary earner, excluding self-employed workers, family workers, and freelance professionals; see Appendix A for details), (iii) reports positive labor earnings, and (iv) reports annual hours of work between 728

and 5096 hours (i.e., weekly hours of work between 14 and 98 hours). For the balanced panels, these requirements need to be satisfied over the entire sample period. For the unbalanced panel, these requirements need to be satisfied for at least five (not necessarily consecutive) years.¹⁹

We adopt requirement (i) in addition to focusing on male earnings, so that an individual in the samples forms a household. Hence, we use the term “households” interchangeably in reference to individuals (husbands) in the following description, hopefully without confusion to readers.²⁰ By construction of the JPSC questionnaire items, requirements (ii) and (iii) exclude student part-time workers and retirees. For this reason, unlike the US literature, we do not further impose an age restriction for the husband. The first wave of the JPSC (i.e., the 1993 survey) does not include questionnaire items about hours worked. We therefore do not impose requirement (iv) on the year 1993. In addition to elimination of households using these requirements, we remove households for which data needed in the calculations are missing, households for which the husband’s age either increases more than a year or remains the same over two years,²¹ households with no information on the husband’s education, and households with extreme values of the husband’s real labor earnings (specifically, a growth rate above 250 percent, below -80 percent, or a level below one million yen in any given year, which were

¹⁹ We discuss later on in Section 4.2 how this restriction on the number of observed years can affect estimation results through a comparison of estimates from the balanced and unbalanced panels.

²⁰ The JPSC questionnaire uses the term “husband” throughout rather than “head of household” or “male household head”. To maintain consistency with the questionnaire, we follow this terminology and do not use the term “head of household” or “male household head” by conscious choice.

²¹ These errors in information on age have been discovered by the author. The response to the author’s inquiries about these errors from the Institute for Research on Household Economics was that they may be modified after reconfirming by further interview. Note that a newly released JPSC CD-ROM (probably after January 2011) may include such corrections. Hence, readers who are interested in replicating our results should pay attention to this point when using the replication programs for this paper, and if the corrections were made, then such readers should modify the programs appropriately. However, we do not expect that it would substantially affect our results because the number of households with these errors in age is small, as described in Appendix B.

decided after examining the empirical distribution of real earnings).

Our sample selection procedure yields 201 households ($201 \times 12 = 2412$ observations) for the 1993–2004 balanced panel, 384 households ($384 \times 8 = 3072$ observations) for the 1997–2004 balanced panel, and 908 households in total (8162 observations) for the 1993–2004 unbalanced panel.²² We further divide each sample into two education groups: college-educated and noncollege-educated groups. We adopt a slightly broad definition of education groups—the “college-educated group” consists of individuals with at least a four-year college degree, and the “noncollege-educated group” consists of individuals without a four-year college degree—in order to avoid a reduction in the sample size for each group in the balanced panels (see Appendix A for details of the definition). Appendix B contains details of the sample selection procedure as well as the number of removed households or observations at each stage.

3.2 Summary Statistics

Table 1 reports summary statistics of our key variables for each of the three types of panel data sets. Panels A, B, and C of Table 1 correspond to those of all individuals, the college-educated group, and the noncollege-educated group, respectively. Here information on pooled data rather than its time series is provided to make it easier to compare the characteristics of the three types of panels and differences between the groups.

²² The length of the time periods in our panels may appear to be short, but it is not necessarily so, compared with those in previous studies. For example, MaCurdy (1982) uses a 10-year panel of earnings. Abowd and Card (1989) use an 11-year panel of earnings and hours worked. Baker (1997) examines a 10-year panel of earnings as well as a 20-year panel. As for the sample size, MaCurdy (1982), for example, studies a balanced panel of 513 continuously married males, and Baker (1997) studies a balanced panel of 534 male household heads, both of which are drawn from the US PSID. Given the difference in the total population between the United States and Japan, it seems fair to state that our sample size of 201 or 384 households is not small. Using Swedish data, Hause (1980), which is one of the early studies supporting profile heterogeneity, examines a panel of 279 males for a period of six years. Thus, the length of our time periods and sample sizes of the balanced panels represent an acceptable lower bound.

The following can be seen from Table 1. First, the husbands of the respondents used for analysis are between 21 and 65 years old and have a mean age that falls into the range of 36 to 39 years old. As mentioned previously, although we have not imposed an age requirement, this age range seems reasonable compared to previous studies. However, we need to note that our samples are slightly weighted toward young age groups. Second, annual labor earnings are higher for the college-educated group than for the noncollege-educated group. On the one hand, annual hours worked (and weekly hours worked) are longer for the noncollege-educated group than for the college-educated group. These facts imply that higher educational attainment results in higher wages (average hourly earnings). Third, labor market experience is longer for the noncollege-educated group than for the college-educated group, which is consistent with the fact that noncollege graduates enter into labor markets earlier. These contrasts suggest that the characteristics of earnings dynamics are different across education groups.

3.3 The Covariance Structures of Earnings

The parameters of interest in this study are ρ , σ_α^2 , σ_ϵ^2 , σ_η^2 , σ_β^2 , and $\sigma_{\alpha\beta}$. They are estimated using information on the variances and autocovariances of the earnings residual. The empirical autocovariance matrix is constructed from the residuals of year-by-year regressions of log real earnings on the common factor $f(X_{it}, \psi_t)$, in which the function $f(\cdot)$ is assumed to be a cubic polynomial in labor market experience.²³

As noted by Guvenen (2009), the coefficients of this polynomial are time varying as a consequence of the year-by-year regression; therefore, the intercept of the function $f(\cdot)$ can be interpreted as capturing time effects (i.e., aggregate shocks common to all individuals). In this

²³ In the US case, Baker (1997) uses a quadratic polynomial in experience, while Haider (2001) uses a quartic polynomial in experience; however, these alternative specifications had no significant effect on the results reported in this paper. In view of this result, it seems that including up to the quadratic term of experience is important at least for analysis based on our data. In the estimation, X_{it}^2 and X_{it}^3 are divided by 10^2 and 10^3 , respectively, as usual.

respect, there is no opportunity to add year dummy variables into our specification. On the other hand, it is possible to add other dummy variables such as cohort, education, and family size into the function $f(\cdot)$, in principle. However, following Guvenen (2009), we do not pursue these alternative specifications with many dummy variables, partly because later we estimate the models after separating the sample into different education groups, and partly because it is difficult to judge which dummy should be added except for the year dummy variables.²⁴

Table 2 presents the variances and autocovariances of the earnings residual calculated using all individuals for each of the three types of panels,²⁵ and Figure 1 plots changes in the variances over the sample period. First, looking at the first column of each panel in Table 2, the variances are significantly different from zero, and as is clear from Figure 1, there is a strong increase in the variances over time. In balanced panels in particular, this increase can be interpreted as indicating that the variation in earnings increases as individuals get older or increase their labor market experience. Second, comparing the magnitude of the variance and its change over time between the balanced and unbalanced panels, the variance as a whole is larger for the unbalanced panel, which implies that this sample contains more heterogeneous individuals. Third, the autocovariances are positive and significantly different from zero. Looking at each row of Table 2 from left to right, it appears that they tend to decline at the first and second orders and then become relatively smooth (although higher-order autocovariances are not reported

²⁴ However, it may be worth including a cohort dummy in the first-stage regression because our two panels (the 1997–2004 balanced panel and the 1993–2004 unbalanced panel) include by construction the two cohorts (cohort A and cohort B). We tried the regression with the cohort dummy, but it did not have a significant effect on the results reported in the next section. On the other hand, we did not try a family size dummy because according to the JPSC questionnaire, our measure of labor earnings does not include child allowance (i.e., it does not depend on the number of children). Consequently, we follow the same specification as Guvenen’s.

²⁵ We estimate cross-sectional variances and autocovariances. See Arellano (2003, p.58) for the definition. There are several ways to obtain the standard errors of the variances and autocovariances in the literature. Here we follow Blundell et al. (2008) and report the estimates and standard errors obtained from regressing $\hat{y}_{it}\hat{y}_{it+j}$ ($j \geq 0$) on a constant term by year.

in the table to save space). Although our data sets are targeted toward Japanese men, these characteristics of autocovariances (excluding their magnitudes) seem similar to those identified in the US literature (e.g., Baker (1997) for balanced panels, Haider (2001) for unbalanced panels) to some extent.

4 Results

In this section, we first present estimation results based on the two balanced panels, and then examine estimates from the unbalanced panel. At the estimation stage, we allow the variance of the transitory shock, σ_ϵ^2 , to vary with time, which is attempted by Guvenen (2009).²⁶ We also attempt to estimate another specification without ϵ_{it} (i.e., that imposes $\sigma_\epsilon^2 = 0$). This specification is close to the case attempted by Baker (1997) and Haider (2001), which enables us to evaluate the effect on the autoregressive parameter of excluding ϵ_{it} .

The parameters of interest are estimated using minimum distance techniques (proposed by Chamberlain (1984)), which minimize the distance between the empirical autocovariance matrix and its counterpart implied by the two models. This approach is widely used in the literature, but as emphasized by MaCurdy (2007, Section 6.6), there is a possibility that the familiar procedures calculate incorrect values of the consistent estimate of the asymptotic variance when unbalanced panel data are used. To avoid this pitfall, we incorporate MaCurdy's suggestions into our estimation procedure based on unbalanced panel data. Details of the estimation method are provided in Appendix C.

²⁶ More correctly, Guvenen (2009) considers the case in which the variance of the transitory component in the AR(1) process, σ_η^2 , as well as the variance σ_ϵ^2 , varies with time. We also tried this case, but it made almost all of the parameter estimates of interest insignificant. Hence, we adopt only the specification with the time-varying σ_ϵ^2 .

4.1 Preliminary Analysis: Estimates from the Balanced Panels

Table 3 reports the results for all individuals based on the two balanced panels. The results of the profile heterogeneity model are provided in panel A of Table 3. For the 1993–2004 panel, the estimate of the autoregressive parameter ρ is 0.595 with a standard error of 0.348 when σ_ϵ^2 is allowed to vary with time; on the other hand, it is 0.384 with a standard error of 0.157 when the specification without ϵ_{it} is used. For the 1997–2004 panel, the estimates of ρ are 0.629 with a standard error of 0.284, and 0.331 with a standard error of 0.136, respectively. Thus, the first finding is that ρ is estimated to be below one in the profile heterogeneity model. If the transitory component ϵ_{it} captures measurement error, then the difference in ρ between the two specifications suggests that the true persistence of earnings shocks will be underestimated by ignoring it.

The estimates of σ_β^2 , which capture heterogeneity in earnings growth rates, are 0.00033 and 0.00044 for the 1993–2004 panel, and 0.00057 and 0.00076 for the 1997–2004 panel. They are all significantly different from zero. Using a balanced panel from the PSID, Baker (1997) obtains estimates of σ_β^2 ranging between 0.00039 and 0.00082. Haider (2001) uses a revolving panel from the PSID and reports an estimate of $\sigma_\beta^2 = 0.00041$. Guvenen (2009) uses unbalanced panels from the PSID and obtains estimates of $\sigma_\beta^2 = 0.00038, 0.00043, \text{ and } 0.00055$ for the case of all individuals. Thus, our result reveals not only that there is statistically significant heterogeneity in earnings growth rates for Japanese men, but also that the magnitude of the estimates is very similar to those obtained from the US data.

The estimates of $\sigma_{\alpha\beta}$ are -0.00339 and -0.00525 for the 1993–2004 panel, and -0.00764 and -0.01093 for the 1997–2004 panel. They are significantly different from zero at conventional significance levels. The negative value of $\sigma_{\alpha\beta}$ implies that the intercept and slope of the earnings profiles are negatively correlated, which is also consistent with the previous work cited above.²⁷

²⁷ Whether $\sigma_{\alpha\beta}$ is negative is of economic interest because it has an important implication that human capital

The estimates of the variance of the fixed effect σ_α^2 are 0.090 and 0.120 for the 1993–2004 panel, and 0.164 and 0.217 for the 1997–2004 panel. Again, they are all estimated to be significantly different from zero. Thus, from the results stated so far, the profile heterogeneity component, $\sigma_\alpha^2 + \sigma_\beta^2 X_{it}^2 + 2\sigma_{\alpha\beta} X_{it}$, has a significant effect on earnings dynamics. On the other hand, the estimates of σ_η^2 are 0.011 and 0.016 for the 1993–2004 panel, and 0.010 and 0.017 for the 1997–2004 panel. Except for one case, they are significantly different from zero. However, given that we have obtained a low estimate of ρ , this result indicates that the AR(1) component (i.e., $\sigma_\eta^2 \times$ the cumulative sum of ρ) as a whole has only a relatively small effect on earnings dynamics.

Another concern here is about how the autoregressive parameter ρ is biased by imposing $\beta_i = 0$. The results of the restricted model are provided in panel B of Table 3. The estimates of ρ are 1.049 with a standard error of 0.057, and 1.026 with a standard error of 0.043, for the 1993–2004 panel. Compared with the corresponding estimates from the profile heterogeneity model (columns (1) and (2)), the estimated persistence rises significantly under the restricted model. This rise is also true for the estimates of ρ from the 1997–2004 panel.

We next turn to the estimation results for the college-educated and noncollege-educated groups. The results are reported in Table 4. Estimation is implemented by applying the same procedure as that for all individuals to each education group separately. As already shown in Table 3, there is a possibility that ignoring the transitory shock ϵ_{it} leads to a bias in the estimate of the autoregressive parameter. Hence, here we focus on the specification that allows σ_ϵ^2 to vary with time.

Panel A of Table 4 reports the results of the profile heterogeneity model. This panel shows that the estimation results differ considerably between the two groups. For the college-educated group, the estimate of ρ is 0.286 for the 1993–2004 panel and 0.493 for the 1997–2004 panel, but

investment (e.g., job training) involves a trade-off between initial earnings and the growth rate of earnings. See Lillard and Weiss (1979) and Hause (1980) for detailed discussions of this interpretation.

they are not significant. For the noncollege-educated group, the estimate of ρ is 0.804 for the 1993–2004 panel and 0.896 for the 1997–2004 panel, both of which are significant. On the one hand, the estimate of σ_β^2 is significant for the college-educated group, but it is not significant for the noncollege-educated group. Similarly, another key parameter of the profile heterogeneity component $\sigma_{\alpha\beta}$ is also significant only for the college-educated group. On the other hand, σ_η^2 is significant only for the noncollege-educated group. Thus, for the noncollege-educated group, there is no evidence in favor of the profile heterogeneity model, in contrast with the college-educated group.

Panel B of Table 4 reports the results of the restricted model. In the restricted model, the parameter estimates are improved overall for the noncollege-educated group, that is, all estimates of ρ , σ_α^2 , and σ_η^2 are significant. This result appears to explain the findings in panel A of Table 4 that failed to accept the profile heterogeneity model for that group. Our finding that the restricted model fits well for the noncollege-educated group seems consistent with, e.g., Carroll and Samwick (1997), who estimate the restricted model with the further restriction of $\rho = 1$ for all educational backgrounds using the US data. However, our result shows that the estimate of ρ is less than one, and the restriction of $\rho = 1$ is not accepted for our data sets. For the college-educated group, the estimate of ρ is significant, but the estimate of σ_η^2 is not significant. In other words, it is difficult to explain the earnings dynamics of the college-educated group using the stochastic component (AR(1) plus transitory shock component). Combined with the finding in panel A of Table 4, this result suggests that profile heterogeneity is still important in modeling the earnings dynamics of the college-educated group.

Our results for each group just reported show that the profile heterogeneity model fails to explain the earnings dynamics of the noncollege-educated group, which is not consistent with Guvenen’s US findings summarized in Section 2. However, it may be premature to draw such a conclusion at this stage of the analysis because our analysis here has the limitation that only

relatively small sample sizes are available for each group (see the last two rows of Table 4 for their sample sizes); that is, information necessary for identifying earnings dynamics for each group may have been eliminated by the loss of observations involving the requirement of balanced panels. Next we turn to the unbalanced panel and examine the robustness of our results.

4.2 Estimates from the Unbalanced Panel

Table 5 reports the results based on the unbalanced panel. As before, we present the results using the specification both with and without ϵ_{it} for all individuals only, to confirm the effect of excluding the transitory shock.

Panel A of Table 5 reports the estimation results of the profile heterogeneity model. As shown in columns (1) and (2) of Table 5, for all individuals the estimate of the autoregressive parameter ρ is 0.688 with a standard error of 0.167 when σ_ϵ^2 is allowed to vary with time, and it is 0.470 with a standard error of 0.077 under the specification without ϵ_{it} . The estimates of ρ are similar to those in panel A of Table 3, but we see that the use of the unbalanced panel yields estimates with sharper standard errors.

The estimates of σ_β^2 are 0.00035 and 0.00034, both of which are significantly different from zero. Again, as in the case of balanced panels (panel A of Table 3), the magnitude of σ_β^2 is comparable to those obtained from the US data. The estimates of $\sigma_{\alpha\beta}$ are -0.00167 and -0.00140 , and the magnitude is reduced relative to those in panel A of Table 3. However, they are still significantly different from zero. The estimates of σ_α^2 and σ_η^2 are also significantly different from zero. Thus, we find that the profile heterogeneity component, $\sigma_\alpha^2 + \sigma_\beta^2 X_{it}^2 + 2\sigma_{\alpha\beta} X_{it}$, as a whole is significantly estimated, regardless of whether balanced or unbalanced panels are used.

A common problem with this type of empirical research (not unique to our work) is the extent to which the sample selection used for analysis has biased the results. The comparison

here between the balanced and the unbalanced panels may also be viewed as a sensitivity analysis for evaluating selection bias caused by eliminating individuals observed for shorter time periods. For example, under the profile heterogeneity model, the estimate of ρ based on the restricted sample (the 1993–2004 balanced panel) is smaller than that of the unrestricted sample (the 1993–2004 *unbalanced* panel). A possible interpretation of this is that the restricted sample has eliminated individuals who suffer more persistent shocks. However, the difference in the estimates is not large. This is also true for the estimate of σ_β^2 . Given these results, although some recent studies require fewer—two, three, or four—years than our requirement of five years to obtain the unbalanced panel (see Haider (2001), Storesletten et al. (2004b), and Guvenen (2009, row (7) of Table 1)), it is unlikely that this slight difference in requirements concerning the number of years observed significantly affects our results.

The difference in the results between the balanced and unbalanced panels appears in the estimation by education group. Columns (3) and (4) of Table 5 report the results for the college-educated and noncollege-educated groups. As we have confirmed that ρ may be underestimated when the transitory shock ϵ_{it} is not allowed for, we concentrate on the results from the specification with ϵ_{it} . As shown in columns (3) and (4) of Table 5, unlike the case of balanced panels (panel A of Table 4), the estimates of ρ are significant, and the estimated persistence is higher for the college-educated group than for the noncollege-educated group: ρ is estimated to be 0.856 with a standard error of 0.144 for the college-educated group and 0.604 with a standard error of 0.259 for the noncollege-educated group.

For the college-educated group, the estimate of σ_β^2 is 0.00032 with a standard error of 0.00018, which is insignificant at the 5% level but significant at the 10% level. For the noncollege-educated group, it is 0.00028 with a standard error of 0.00005. Thus, in our case there seems *not* to be a significant difference in the dispersion of earnings growth rates between the two groups. This point is reexamined from a slightly different perspective in Section 4.3. The estimates of $\sigma_{\alpha\beta}$ are

-0.00232 and -0.00166 for the college-educated and noncollege-educated groups, respectively, both of which are significantly different from zero. This finding that $\sigma_{\alpha\beta}$ is more negative for highly educated individuals is consistent with Guvenen (2009), whose interpretation is that the accumulation of human capital may be more important for high-skilled occupations for raising future earnings (wage growth) (also see Hause (1980)). We also see from the table that the parameter σ_η^2 is significantly estimated for both education groups, unlike the case of balanced panels.

An important point to note in panel A of Table 5 is that σ_α^2 is significantly estimated even under the profile heterogeneity model, which is different from Guvenen (2009). In our case, the estimate of σ_α^2 is 0.030 with a standard error of 0.008, or 0.026 with a standard error of 0.009 for all individuals, and it is 0.039 with a standard error of 0.013 for the college-educated group, and 0.024 with a standard error of 0.009 for the noncollege-educated group. In contrast, Guvenen (2009) finds that the estimates of σ_α^2 are 0.022, 0.023, and 0.038 for all individuals, the college-educated group, and the high-school-educated group, respectively, which are similar to ours in terms of magnitude, but are *not* significantly different from zero. This contrast suggests that in our case the fixed effect (i.e., initial conditions at the time when individuals enter into labor markets) can also account for heterogeneity in earnings, in addition to the dispersion of earnings growth rates.

Panel B of Table 5 reports the estimation results of the restricted model. Columns (5) and (6) of Table 5 report the results for all individuals, and columns (7) and (8) of Table 5 report the results by education group. As expected, the estimates of ρ go up relative to those of the profile heterogeneity model: from 0.688 to 0.900 or 0.470 to 0.860 for all individuals; from 0.856 to 0.904 for the college-educated group; and from 0.604 to 0.873 for the noncollege-educated group. There are two points to note here. First, the rise in ρ under the restricted model for the college-educated group is very small relative to those for all individuals and the noncollege-

educated group. Second, the magnitude of the estimated ρ as a whole seems lower than that in the balanced panels (e.g., panel B of Table 3). To understand these points, it is necessary to allow for the magnitude of the estimate of σ_η^2 simultaneously, because the effect of the stochastic shock η_{it} on the variances and autocovariances of the earnings residual appears as $\sigma_\eta^2 \times$ the cumulative sum of ρ , as in equation (4). For example, if the estimate of σ_η^2 is higher, then the estimate of ρ is expected to be lower, other things being equal.

Looking at panels A and B of Table 5 again with this point in mind, while the estimate of σ_η^2 increases from 0.006 to 0.011 for the college-educated group (columns (3) and (7)), it remains at almost the same magnitude for all individuals and the noncollege-educated group. This difference probably accounts for the first point to some extent. On the other hand, looking at panel B of Table 3 once again, while the estimate of σ_η^2 under the restricted model falls into the range of 0.003 to 0.011, it is between 0.011 and 0.020 in panel B of Table 5. That is, one reason why we have obtained the lower estimates of ρ in the estimation of the restricted model based on the unbalanced panel can be related to the higher magnitude of σ_η^2 . However, it is noteworthy that even in our case we have found that ignoring profile heterogeneity leads to an upward bias in ρ .

Another noteworthy point in panel B of Table 5 is that, as seen from a comparison between columns (7) and (8), overall, there is little difference in the estimated parameters between the two groups. In other words, it reveals that the use of the restricted model obscures the difference between the two groups.

In summary, we obtain three main findings from the analysis so far. First, an increase in the variance of the earnings residual over time can also be observed in our data on Japanese individuals, and when we attempt to explain this increase using the models, ignoring profile heterogeneity (especially, the dispersion of earnings growth rates) by assuming the restricted model leads to a substantial upward bias in the persistence of earnings shocks. Second, according

to our estimation by education group based on the unbalanced panel, the profile heterogeneity model fits well for both the college-educated and noncollege-educated groups as well as all individuals. However, we cannot find a significant difference in the dispersion of earnings growth rates between the two groups (although its estimate is very slightly larger for the college-educated group than for the noncollege-educated group). This is inconsistent with Guvenen’s US findings. Third, the individual fixed effect is significant not only in the restricted model but also in the profile heterogeneity model. This also contrasts with Guvenen’s US findings.

4.3 Discussion

4.3.1 Alternative Grouping and Occupational Differences

Our second result is different from the corresponding US finding. Here we examine two factors that may cause a bias in the parameter σ_β^2 . The first factor is that our grouping “noncollege-educated group” includes non-high school graduates (i.e., those who did not graduate from high school). As mentioned previously, this grouping was adopted for the purpose of securing an adequate sample size for the balanced panel data. However, we can now relax this restriction of grouping by the use of the unbalanced panel.

Panel A of Table 6 reports the estimation result of the profile heterogeneity model for the high-school-educated group (defined by removing non-high school graduates from the noncollege-educated group). As a reduction in the total sample size by this elimination of non-high school graduates, which is confirmed in the last two rows, may change the estimates for all individuals in column (1) of Table 5, we also implement estimation for all individuals of the new sample (composed of the college-educated group and the high-school-educated group). Initial earnings and earnings growth rates of junior high school graduates are usually lower than those of high school graduates. Therefore, the inclusion of non-high school graduates increases variation in earnings, and consequently, it may lead to an upward bias in the estimate of σ_β^2 (and σ_α^2) for the noncollege-educated group. The result in column (1) of Table 6 shows that this conjecture

indeed holds for our data set: the estimate of σ_β^2 decreases from 0.00028 to 0.00025 when the high-school-educated group is used instead of the noncollege-educated group. As expected from this result, the estimate of σ_β^2 based on all individuals in column (2) of Table 6 also slightly decreases from 0.00035 (in column (1) of Table 5) to 0.00030. Thus, the earlier finding that the difference in σ_β^2 between the two education groups is very small is partly attributable to the upward bias in σ_β^2 caused by the inclusion of non-high school graduates. However, the difference in σ_β^2 between the college-educated and high-school-educated groups (i.e., 0.00032 and 0.00025) still remains small compared with Guvenen’s finding for the United States (i.e., 0.00049 and 0.00020).

The second factor is treatment of occupations. As Topel (1991, p.164) puts it, “It is not hard to imagine technological or other differences across occupations that would generate corresponding differences in wage profiles.” It is possible to consider this in our context: even if individuals have the same education background (or skill if education is its indicator), differences in occupations (e.g., clerical jobs and technical jobs) would cause variation in initial earnings (i.e., σ_α^2) and in earnings growth rates (i.e., σ_β^2) to be larger if they were not controlled for. To see how the earlier finding is related to the failure in allowing for occupational differences in earnings profiles, we further attempt to control for its effect by including occupation dummy variables in the first-stage regression (see Appendix A for details of categories of occupations). Panel B of Table 6 reports the estimation results of the profile heterogeneity model for five cases: all individuals of the original sample (the college-educated group plus the noncollege-educated group), all individuals of the new sample (the college-educated group plus the high-school-educated group), the college-educated group, the noncollege-educated group, and the high-school-educated group. We obtain two findings from this exercise. First, the magnitude of the estimate of σ_β^2 as a whole becomes smaller. In other words, this result suggests that the magnitude of the estimate of σ_β^2 that we previously obtained in Table 5 had partially reflected occupational differences in earn-

ings growth rates. However, more importantly, σ_β^2 is again estimated to be significantly different from zero even in this case. Second, comparing the estimate of σ_β^2 between the college-educated and noncollege-educated groups (column (5) and column (6)) or between the college-graduated and high-school-educated groups (column (5) and column (7)), we see that the difference is still small.²⁸ Thus, it is difficult to conclude that the failure of grouping or allowing for occupational differences in earnings dynamics has obscured the existence of a significant difference in the parameter σ_β^2 across education groups, as long as our data set is used.

4.3.2 Identification Problem

A final concern is that the results reported in Table 3 and Table 5 do not appear to reject either of the two models in terms of the significance of the estimates. One way to evaluate our results from a different perspective, which was proposed in the literature (e.g., MaCurdy (1982) and Abowd and Card (1989)), will be to use an approach that examines the signs of the autocovariances of the first difference of \hat{y}_{it} . In our models, the autocovariances between $\Delta\hat{y}_{i2}$ and $\Delta\hat{y}_{is}$ are given by:

$$\text{Cov}(\Delta\hat{y}_{i2}, \Delta\hat{y}_{is}) = \sigma_\beta^2 + \text{Cov}(\Delta z_{i2}, \Delta z_{is}), \quad (6)$$

for $s > 2$. For example, $\Delta\hat{y}_{i2}$ corresponds to $\Delta\hat{y}_{i,1994}$ for the 1993–2004 panel. If $\rho = 1$, then the second term on the right-hand side is zero because the shock η_{it} follows a white noise process in that case. Moreover, if one considers the restricted model, then the right-hand side as a whole is zero because of $\sigma_\beta^2 = 0$ by assumption. Therefore, the basic idea of the alternative way is to test whether the autocovariances of the first difference of \hat{y}_{it} are zero or not. As discussed in Guvenen (2009), however, it is extremely difficult to distinguish a very small value of σ_β^2 such

²⁸ Note that this result about the variance does not mean that there exists no wage premium associated with a college education in Japan because as described in Section 3.2, the summary statistics for our data suggest that the average wage for a worker with a college-level education is higher than the average wage for a high school graduate.

as 0.00032 from zero. As our estimate of σ_β^2 is quite similar to the US case, this issue also holds for our case.

As mentioned in the Introduction, this difficulty of distinguishing one model from the other model has motivated a new literature that includes Guvenen and Smith (2009), who propose using information from consumption data as well as labor earnings data. Thus, drawing only the conclusion that the results in this paper support the profile heterogeneity model should be avoided, but at the same time, it is also true for the near unit root and unit root models: an impartial view is that, similarly, it is difficult to justify the highly persistent assumption of earnings shocks by the finding that the restricted model is not rejected.

5 Conclusion

The recent empirical work on earnings processes by Guvenen (2009) argues that the existing assumptions in incomplete markets models, which require highly persistent earnings shocks and no individual-specific differences in earnings growth rates, may be inappropriate. In this paper, we estimated the profile heterogeneity model and the restricted model using Japanese panel data, and we found empirical evidence in favor of this argument. However, we failed to find support for another argument that there is a significant difference in the dispersion of earnings growth rates between the college-educated and noncollege-educated groups, although our results indicate that the magnitude of the dispersion parameter seems slightly larger for the college-educated group than for the noncollege-educated group.

We also found that, together with evidence of a moderate earnings shock and a significant dispersion of earnings growth rates for each education group, the fixed effect is significantly estimated even when the profile heterogeneity model is used, suggesting that the initial conditions at the time when individuals enter into labor markets are also important for earnings dynamics. Our results seem to be compatible with the observations (in Japanese labor markets) that initial

salaries differ across educational backgrounds or kinds of occupation, and that salary increases also differ depending on individual-specific factors, such as ability. These observations are difficult to explain using the restricted model that does not allow for profile heterogeneity; however, we argued that the restricted model also could not be rejected, which is an impartial view of our empirical results. There are some differences between our estimates and Guvenen's. Nevertheless, the general message from our analysis in this paper is similar to that drawn from Guvenen's findings for the United States: the empirical evidence offers no support for the modeling strategy (of earnings processes) that excludes profile heterogeneity by assumption.

Appendix

This appendix contains three sections. Section A provides the definitions of the variables used in the analysis. Section B describes in detail how we created the three panel data sets. Section C explains the estimation procedure.

A. Definition of Variables

In October 2008 (i.e., the time we obtained permission to use the data), the JPSC CD-ROM provided by the Institute for Research on Household Economics contains data for the period from 1993 to 2004 (12 waves). When describing the source of the variables below, we follow the number assigned to the questionnaire items in the survey sheet of 2004, unless otherwise noted, and denote it by “Item xx, Question yy”. In addition to this, we also report the associated variable name in 2004, which is not listed in the survey sheet but assigned in the JPSC CD-ROM, for ease of reference. If the questionnaire items were not included in the 2004 survey, we follow the latest survey including them. The 2004 survey sheet is downloadable both in Japanese and in English from the Web site of the Institute for Research on Household Economics (<http://www.kakeiken.or.jp/en/>).

Survey sheets referred. As described in the text, respondents of the JPSC are women, and if they are married, they are then asked about their husband. For this reason, if we access the above-mentioned Web site or open up the folder (named p12 for the 2004 survey) that contains survey sheets in the JPSC CD-ROM, there are three types of survey sheets: for married women, for women with no spouse, and for women who got married in the past year (i.e., women who were married after the survey in the previous year).²⁹ The survey sheet that we refer to below is the one for married women, unless otherwise noted because we focus on male earnings.

Age. Husband’s age is available from Item 1, Question 2 (variable name q13) if the respondent is married.

²⁹ Unfortunately, the JPSC CD-ROM (at least the version provided to the author) does not contain the survey sheets translated into English. The English version of the survey sheets is available only from the Web site of the Institute for Research on Household Economics at the time of writing.

Annual labor earnings. Husband’s labor earnings are earnings before tax from employment, available from Item 6, Question 3 (variable name q296a), in which respondents are asked the annual amount of earnings for the *preceding* calendar year.³⁰ For example, labor earnings in the 1994 survey correspond to those obtained from January 1993 to December 1993. To convert to real terms, the nominal values are divided by the consumer price index (calendar year average of general index, 2005 constant price) compiled by the Statistics Bureau in the Ministry of Internal Affairs and Communication of the Japanese government.

Annual hours worked. The JPSC does not have a questionnaire item that asks directly for the annual hours worked. Instead, respondents are asked their husband’s categorized hours worked per week and daily living schedule, as well as their own. The husband’s annual hours worked are calculated using these questionnaire items in the following way. The other calculation methods and their potential issues are discussed in Section B.4.

Step 1: We calculate total hours worked per week as: total hours worked per week = hours worked on weekdays \times (7 – the number of holidays per week), where “hours worked on weekdays” is available from Item 15, Question 1 (variable name q495bh for hours and q495bm for minutes) and “the number of holidays per week” is from Item 14, Question 2 (variable name q498a in 2002). Although “hours worked on weekdays” are available in all years, “the number of holidays per week” is not available in 2003 and 2004. We assume that the numbers of holidays per week in 2003 and 2004 are the same as that in 2002.

Step 2: In Item 4, Question 8 (variable name q223), respondents report their husband’s hours worked per week by selecting one of 10 categories (1. less than 15 hours, 2. 15 to 21 hours, 3. 22 to 34 hours, 4. 35 to 42 hours, 5. 43 to 45 hours, 6. 46 to 48 hours, 7. 49 to 54 hours, 8. 55 to 59 hours, 9. 60 to 64 hours, 10. over 64 hours). If the calculated hours worked per week in Step 1 exceed the upper limit of the categorized hours worked per week that the

³⁰ Although this question in the JPSC does not necessarily provide detailed information about components of earnings, judging from the form of the question it seems appropriate to assume that bonuses and overtime are included.

respondent reported, then we set it to the value of the upper limit. Conversely, if it is below the lower limit of the category, then we set it to the value of the lower limit. For example, if a respondent reports category 6 (i.e., 46 to 48 hours), but the calculated hours worked per week is 50 hours, then we set her husband’s total hours worked per week to 48 hours.

Step 3: Judging from the JPSC questionnaire, the problem with using “hours worked on weekdays” and “categorized hours worked per week” is that they may include hours of unpaid overtime or service overtime work. The JPSC has a question item that asks hours of unpaid overtime or service overtime work per week (Item 4, Question 9(2), variable name q225). It consists of eight categories (1. 0 hour, 2. 1 to 3 hours, 3. 4 to 5 hours, 4. 6 to 10 hours, 5. 11 to 15 hours, 6. 16 to 20 hours, 7. 21 hours or more, 8. no service overtime work), and respondents select one category from them.³¹ Using this information, hours worked per week are calculated as: $\text{hours worked per week} = \text{total hours worked per week} - \text{average hours of overtime work per week}$, where “average hours of overtime work per week” are defined as $(\text{the lower limit} + \text{the upper limit in the reported category})/2$. For category 7, which does not have the upper limit, we assume that average hours of overtime work per week are 21.

Step 4: Using the hours worked per week calculated in the first three steps, annual hours worked are calculated as: $\text{annual hours worked} = \text{hours worked per week} \times 52$, where 52 is the number of weeks per year computed as 365 days/7 days.

Labor market experience. There is a question that asks how long the husband has worked since graduation from school; however, this is only in the first survey for each cohort (i.e., in the 1993 survey for cohort A and in the 1997 survey for cohort B) or in an additional survey sheet for respondents who were married after the survey in the previous year. It is labeled as Item 8, Question 1 in the 1993 survey sheet, Item 6, Question 1 in the 1997 survey sheet, and Item 2, Question 1 in the survey sheet for those who were married after the survey in the previous year (variable name q689a for years and q689b for months). The husband’s labor market experience

³¹ The eighth category (i.e., 8. no service overtime work) was added in the 2003 survey, so that until the 2002 survey this question item consists of only the first seven categories.

is calculated by adding one to the number of years worked (calculated as $q689a + q689b/12$) if the respondent answers that her husband currently works in Item 4, Question 1 (variable name $q213$).

Education. Husband’s educational background is based on the categorical data created using the relevant questionnaire items by the Institute for Research on Household Economics (variable name $q61sr$). It consists of eight categories (1. junior high school, 2. vocational school, 3. high school, 4. both vocational school and high school, 5. junior college or specialized vocational high school, 6. 4-year college, 7. graduate school, 8. no response). We define the husband’s education group as “college-educated group” if this variable is 6 or 7 and as “noncollege-educated group” if it is 1, 2, 3, 4, or 5. We define categories 1 and 2 as “non-high school graduate”.

Occupation. Husband’s occupation is provided in Item 4, Question 3 (variable name $q860$). The definition of an employee in this question of the JPSC includes the following: 6. Management (on a higher level than a manager in a company or organization, or a head of section in a public agency), 7. Other professionals (hospital doctor, researcher, professor, assistant professor or tutor in university or college, judge, etc.), 8. Technical employee (engineer, technician, programmer, medical nurse, dietitian, etc.), 9. Teacher (in primary, junior high school, senior high school, special or professional school, kindergarten or day nursery), 10. Clerical employee (general clerk, business employee, bank clerk, etc.), 11. Skilled employee (skilled worker, police, deliveryman, motorman, artisan, etc.), 12. Sales and service employee (shop employee, salesperson, barber or hairdresser, chef, waiter, home helper, etc.), where the numbers (6 to 12) assigned to each category follow those of the survey sheet.

B. Derivation of Samples

This section describes in detail how we derived the three samples from the raw data. The deletion of households based on requirements (i)–(iv) involves, e.g., elimination of households with missing values for relevant variables, so that a few preliminary steps are required at each

stage. As the following includes detailed descriptions of such steps, Appendix Figure 1 provides a brief summary to make it easier to understand the process of the derivation.

B.1 The 1993–2004 Balanced Panel

From the original 1500 respondents in the JPSC, we removed the following households:

Singles and not continuously married couples. We removed singles or couples with changes in marital status during 1993–2004 and kept only continuously married couples for that period. The marital status can be judged from the categorical data created using the relevant questionnaire items by the Institute for Research on Household Economics (variable name q1). This deletion leaves us with 592 households.

Households for which the husband is not employed. We removed 70 households with periods in which the husband did not work or with missing data on the husband’s labor force status. The information on the husband’s labor force status is available from Item 4, Question 1 (variable name q213). We then removed 140 households for which the husband is a self-employed worker, a family worker, or a freelance and kept households for which the husband is classified as an “employee” for every year of the sample period. The definition of “employee” follows that in the JPSC, which corresponds to categories 6 to 12 in Item 4, Question 3 (variable name q860), as described in Appendix A. This leaves us with 382 households.

Households for which the husband has nonpositive earnings. We removed 106 households for which the husband’s labor earnings are not positive or recorded as 9999 and kept households with positive earnings for the husband for every year of the sample period. This leaves us with 276 households.

Households with missing data on the husband’s hours worked and labor market experience. We removed 53 households for which the variables needed to construct the husband’s annual hours worked and labor market experience are not available. In the JPSC, those missing cases are recorded as 11 for q223, 8 (9 in 2003 and 2004) for q225, 99 for q495bh, 9 for q495bm, 99 for q498a, and 99 for q689a and q689b. This leaves us with 223 households.

Households with extreme hours worked for the husband. We removed 14 households with the husband's annual hours worked > 5096 (98 hours per week) or < 728 (14 hours per week), which leaves us with 209 households.

Households with inconsistency between the husband's age and labor market experience. We removed three households for which the husband's age increases more than a year or remains the same over two years, which leaves us with 206 households.

Households with missing data on the husband's education. There were no households removed by this criterion.

Households with outliers. We removed five households with an extreme growth rate of real earnings (above 250 percent or below -80 percent) or with an extreme value of real earnings that is one digit smaller in any given year (the latter case was deleted by imposing real earnings $< \text{one million yen}$).

The sample selection procedure stated so far leaves us with a sample of 201 households. The total number of observations is $201 \times 12 = 2412$.

B.2 The 1997–2004 Balanced Panel

To construct a panel for the period 1997–2004, we need to note the following: (i) if respondents are married as of the first survey of 1993 for cohort A and 1997 for cohort B, then they are asked how long the husband has worked since graduation from school; (ii) after that survey, the same question is asked using an additional survey sheet only when they are newly married. Thus, by construction, the variables needed to calculate the husband's labor market experience appear only once for each respondent (unless they get divorced and remarry in the sample period). As a result, the sample selection procedure needs to include the calculation of the husband's labor market experience before deleting the period 1993–1996. From 2000 respondents, composed of 1500 from cohort A and 500 from cohort B, we removed the following households:

Singles. We removed singles and kept only married couples. This leaves us with 1550 households.

Households with missing data on the husband’s labor market experience. We removed 43 households for which the variables needed to calculate the husband’s labor market experience are recorded as 99 or missing.

Households with inconsistency between the husband’s age and labor market experience. We removed 12 households for which the husband’s age increases more than a year or remains the same over two years, which leaves us with 1495 households.

Period 1993–1996. After calculating the husband’s labor market experience, we removed observations of the period 1993–1996.

After the above preparation, the sample selection proceeds as in the case of the 1993–2004 panel.

Not continuously married couples. We kept only continuously married couples for the period 1997–2004, leaving us with 804 households.

Households for which the husband is not employed. We removed 74 households with periods in which the husband did not work or with missing data on the husband’s labor force status. We then removed 156 households and kept households for which the husband is classified as an “employee” in the definition of the JPSC for every year of the period 1997–2004. This leaves us with 574 households.

Households for which the husband has nonpositive earnings. We removed 112 households for which the husband’s earnings are not positive or recorded as 9999 and kept households with positive earnings for the husband for every year of the sample period. This leaves us with 462 households.

Households with missing data or extreme values for the husband’s hours worked. We removed 55 households for which the variables needed to calculate the husband’s annual hours worked are not available. We then removed 18 households with the husband’s annual hours worked > 5096 or < 728 . This leaves us with 389 households.

Households with missing data on the husband’s education. We removed one household with no information about the husband’s education, which leaves us with 388 households.

Households with outliers. We removed four households with an extreme growth rate of real earnings (above 250 percent or below -80 percent) or with an extreme value of real earnings below one million yen.

This sample selection procedure leaves us with a sample of 384 households ($384 \times 8 = 3072$ observations).

B.3 The 1993–2004 Unbalanced Panel

For the same reason as that mentioned in the first paragraph of Section B.2, we need to calculate the husband’s labor market experience and then implement the sample selection. From the sample of 2000 respondents, we first removed the following households:

Singles. We removed singles and kept only married couples. This leaves us with 1550 households.

Households with missing data on the husband’s labor market experience. We removed 43 households for which the variables needed to calculate the husband’s labor market experience are recorded as 99 or missing.

Households with inconsistency between the husband’s age and labor market experience. We removed 12 households for which the husband’s age increases more than a year or remains the same over two years, leaving us with 1495 households.

After calculating the husband’s labor market experience for this sample, we remove households that do not satisfy the conditions as in the previous procedures. However, note that, *unlike* the case of the balanced panels, removing a household in any given year does not necessarily mean that the household is completely deleted from the final sample because we do not require that the conditions are satisfied over the entire sample period. Allowing for this difference between balanced and unbalanced panels, we report the number of observations removed or kept at each stage of the sample selection procedure and finally provide the total number of households included in the analysis.

Households for which the husband is not employed. We removed 5824 observations

of households with periods in which the husband did not work or with missing data on the husband’s labor force status. We then removed 1870 observations and kept observations of households for which the husband is classified as an “employee”. This leaves us with 10246 observations.

Households for which the husband has nonpositive earnings. We removed 633 observations of households for which the husband’s earnings are not positive or recorded as 9999 and kept observations of households with positive earnings for the husband. This leaves us with 9613 observations.

Households with missing data or extreme values for the husband’s hours worked. We removed 438 observations of households for which the variables needed to calculate the husband’s annual hours worked are not available. We then removed 52 observations of households with the husband’s annual hours worked > 5096 or < 728 . This leaves us with 9123 observations.

Households with missing data on the husband’s education. We removed two observations of households with no information about the husband’s education, leaving us with 9121 observations.

Households with outliers. We removed 41 observations of households with an extreme growth rate of real earnings (above 250 percent or below -80 percent) or with an extreme value of real earnings below one million yen, which leaves us with 9080 observations.

Households for which the observed number of years is less than five. From the sample obtained thus far, we finally removed 918 observations of households for which the observed number of years is less than five and kept households satisfying the requirements for at least five years, which leaves us with 8162 observations.

This sample selection procedure leaves us with 908 households in total.

B.4 Sample Selection Using Different Calculation Methods of Annual Hours Worked

The calculation of annual hours worked in this paper is not the only feasible approach. Perhaps the simplest way is to use only the categorized hours worked per week and, e.g., to calculate

(the lower limit + the upper limit)/2 for each of the 10 categories. However, as is readily understood, this approach appears to smooth changes in hours worked per week (and hence annual hours worked) excessively over time. In addition, as shown in step 2 of our calculation of hours worked, the range of hours is different among the 10 categories, which also appears to introduce a measurement error in the calculated hours worked per week (and hence annual hours worked). Another possible way may be to use Item 4, Question 10, in which respondents report how many days the husband worked in the previous year by selecting one of 10 categories (1. less than 50 days, 2. 50 to 99 days, 3. 100 to 149 days, 4. 150 to 174 days, 5. 175 to 199 days, 6. 200 to 224 days, 7. 225 to 249 days, 8. 250 to 274 days, 9. 275 to 299 days, 10. 300 days or more), and to calculate annual hours worked as hours worked on weekdays \times this number of days, under additional assumptions such as (the lower limit + the upper limit)/2. Obviously, this approach will also introduce a measurement error because the ranges of days are large and differ among the 10 categories. Unfortunately, it is difficult to judge what is the best method. For this reason, we adopted an approach that uses as much information as possible to obtain annual hours worked, and thereby eliminates the respondents with inconsistencies between the different questionnaire items about the husband's hours worked, unlike the two approaches above.

C. The Estimation Method

In this section, we first review the familiar approach to balanced panel data, and then describe how it should be modified to carry out MaCurdy's (2007) recommendation.³²

³² In this paper, we follow a common practice in recent work, especially Haider (2001) and Guvenen (2009). Unfortunately, they do not provide enough information about the calculation method of the consistent estimator of the asymptotic variance exploited when computing standard errors of parameter estimates. For example, it is difficult to judge whether the statements that "Both expectations are replaced by sample averages when implemented" (Guvenen 2009, p.78) and "Finally, we estimate Φ and D with their simple empirical analogs" (Haider 2001, p.830) mean the same calculation as those of the matrices $\hat{\mathbf{G}}^*$, $\hat{\mathbf{S}}^*$, and $\mathbf{D}^*\hat{\mathbf{S}}^*\mathbf{D}^*$ described below. Therefore, although some of descriptions in this appendix (in particular, Appendix C.1) are expected to be familiar enough, it is still worth repeating them for clarification of MaCurdy's points.

C.1 Balanced Panel

Let \hat{y}_{it} be the earnings residual of individual i in year t , obtained by regressing y_{it} on the polynomial function $f(X_{it}, \psi_t)$. Suppose that the covariance matrix of a $T \times 1$ time series $\hat{\mathbf{y}}_i = (\hat{y}_{i1}, \hat{y}_{i2}, \dots, \hat{y}_{iT})'$ is a function of a $p \times 1$ parameter vector $\boldsymbol{\theta}$, given by:

$$E(\hat{\mathbf{y}}_i \hat{\mathbf{y}}_i') = \boldsymbol{\Omega}_i(\boldsymbol{\theta}) \quad (i = 1, 2, \dots, n),$$

where the diagonal elements are:

$$\text{Var}(\hat{y}_{it}) = \sigma_\alpha^2 + \sigma_\epsilon^2 + \sigma_\eta^2 \sum_{j=0}^{t-1} \rho^{2j} + (\sigma_\beta^2 X_{it}^2 + 2\sigma_{\alpha\beta} X_{it}),$$

and the off-diagonal elements are:

$$\text{Cov}(\hat{y}_{it}, \hat{y}_{is}) = \sigma_\alpha^2 + \sigma_\eta^2 \rho^{|t-s|} \sum_{j=0}^{t-1} \rho^{2j} + [\sigma_\beta^2 X_{it} X_{is} + \sigma_{\alpha\beta} (X_{it} + X_{is})] \quad (s \neq t),$$

so that the parameter vector to be estimated is $\boldsymbol{\theta} = (\rho, \sigma_\alpha^2, \sigma_\epsilon^2, \sigma_\eta^2, \sigma_\beta^2, \sigma_{\alpha\beta})'$ for the profile heterogeneity model; on the other hand, it is $\boldsymbol{\theta} = (\rho, \sigma_\alpha^2, \sigma_\epsilon^2, \sigma_\eta^2)'$ for the restricted model because of $\sigma_\beta^2 = 0$ and $\sigma_{\alpha\beta} = 0$. When σ_ϵ^2 is allowed to vary with time, it is replaced with the parameter vector $(\sigma_{\epsilon,1}^2, \sigma_{\epsilon,2}^2, \dots, \sigma_{\epsilon,T}^2)'$, whose dimension depends on the length of the sample period.

Now let \mathbf{c}_i be an $L(\equiv T(T+1)/2) \times 1$ vector of unique elements of $\hat{\mathbf{y}}_i \hat{\mathbf{y}}_i'$. Using the vech operator that stacks by row the lower triangle elements of a square matrix, we define the $L \times 1$ vector as:

$$\begin{aligned} \mathbf{c}_i &\equiv \text{vech } \hat{\mathbf{y}}_i \hat{\mathbf{y}}_i' \\ &= (\hat{y}_{i1}^2, \hat{y}_{i1}\hat{y}_{i2}, \hat{y}_{i2}^2, \dots, \hat{y}_{iT}\hat{y}_{i1}, \hat{y}_{iT}\hat{y}_{i2}, \dots, \hat{y}_{iT}^2)'. \end{aligned}$$

Similarly, we define an $L \times 1$ vector of unique elements of the covariance matrix $\boldsymbol{\Omega}_i(\boldsymbol{\theta})$ as:

$$\boldsymbol{\omega}_i(\boldsymbol{\theta}) \equiv \text{vech } \boldsymbol{\Omega}_i(\boldsymbol{\theta}).$$

Letting $\mathbf{g}_i(\boldsymbol{\theta}) \equiv \mathbf{c}_i - \boldsymbol{\omega}_i(\boldsymbol{\theta})$ and denoting the l -th element of $\mathbf{g}_i(\boldsymbol{\theta})$ by $g_{il}(\boldsymbol{\theta})$, we consider the following moment conditions:

$$E[\mathbf{g}_i(\boldsymbol{\theta}_0)] = \mathbf{0},$$

where $\boldsymbol{\theta}_0$ is the true parameter value of $\boldsymbol{\theta}$.

The generalized method of moments (GMM) estimator $\hat{\boldsymbol{\theta}}$ is a solution that minimizes the objective function:

$$\left[\frac{1}{n} \sum_{i=1}^n \mathbf{g}_i(\boldsymbol{\theta}) \right]' \widehat{\mathbf{W}} \left[\frac{1}{n} \sum_{i=1}^n \mathbf{g}_i(\boldsymbol{\theta}) \right],$$

and under a set of appropriate regularity conditions including $\frac{1}{\sqrt{n}} \sum_{i=1}^n \mathbf{g}_i(\boldsymbol{\theta}_0) \rightarrow_d N(\mathbf{0}, \mathbf{S})$, it is asymptotically normal: $\sqrt{n}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0) \rightarrow_d N(\mathbf{0}, \mathbf{V})$. An optimal choice of the weighting matrix $\widehat{\mathbf{W}}$ is $\widehat{\mathbf{S}}^{-1}$, the inverse of the sample counterpart of $\mathbf{S} \equiv E[\mathbf{g}_i(\boldsymbol{\theta}_0)\mathbf{g}_i(\boldsymbol{\theta}_0)']$ (under iid assumption of the data vector). However, it is known that the GMM estimator with this optimal weight exhibits poor small-sample properties in the context of estimating covariance structures (Altonji and Segal (1996)). Therefore, we follow the practice of papers in this area and replace $\widehat{\mathbf{W}}$ by the identity matrix.³³ In this case, the expression for the asymptotic variance reduces to $\mathbf{V} = (\mathbf{G}'\mathbf{G})^{-1}\mathbf{G}'\mathbf{S}\mathbf{G}(\mathbf{G}'\mathbf{G})^{-1}$, which is consistently estimated by:

$$\widehat{\mathbf{G}} \equiv \frac{1}{n} \sum_{i=1}^n \frac{\partial \mathbf{g}_i(\hat{\boldsymbol{\theta}})}{\partial \boldsymbol{\theta}'} \quad \text{and} \quad \widehat{\mathbf{S}} \equiv \frac{1}{n} \sum_{i=1}^n \mathbf{g}_i(\hat{\boldsymbol{\theta}})\mathbf{g}_i(\hat{\boldsymbol{\theta}})'.$$

The approximate distribution for $\hat{\boldsymbol{\theta}}$ is:

$$\hat{\boldsymbol{\theta}} \sim N(\boldsymbol{\theta}_0, \frac{1}{n}(\widehat{\mathbf{G}}'\widehat{\mathbf{G}})^{-1}\widehat{\mathbf{G}}'\widehat{\mathbf{S}}\widehat{\mathbf{G}}(\widehat{\mathbf{G}}'\widehat{\mathbf{G}})^{-1}).$$

Standard errors are calculated as the square root of the diagonal elements of $\frac{1}{n}(\widehat{\mathbf{G}}'\widehat{\mathbf{G}})^{-1}\widehat{\mathbf{G}}'\widehat{\mathbf{S}}\widehat{\mathbf{G}}(\widehat{\mathbf{G}}'\widehat{\mathbf{G}})^{-1}$.

C.2 Unbalanced Panel

We allow the panel to be unbalanced in that individuals may not be observed every year (i.e., some rows of \mathbf{c}_i and $\boldsymbol{\omega}_i(\boldsymbol{\theta})$ may not be available). To handle missing observations, we define an indicator variable, d_{il} , as:

$$d_{il} = \begin{cases} 1 & \text{if individual } i \text{ contributes to the } l\text{-th moment,} \\ 0 & \text{otherwise,} \end{cases}$$

³³ As discussed by Newey and McFadden (1994), GMM is a special case of minimum distance (MD) estimation; therefore, the GMM estimator with the optimal weighting matrix $\widehat{\mathbf{W}} = \widehat{\mathbf{S}}^{-1}$ is often referred to as the optimal minimum distance (OMD) estimator, especially in the literature on covariance structures (see, e.g., Altonji and Segal (1996)). Furthermore, this approach, which uses the identity matrix as the weighting matrix, is often called equally weighted minimum distance (EWMD) estimation. Following Newey and McFadden (1994), we use the term GMM because the objective function is defined using a sample mean.

and let:

$$\mathbf{g}_i^*(\boldsymbol{\theta}) \equiv \begin{bmatrix} d_{i1}g_{i1}(\boldsymbol{\theta}) \\ d_{i2}g_{i2}(\boldsymbol{\theta}) \\ \vdots \\ d_{iL}g_{iL}(\boldsymbol{\theta}) \end{bmatrix} = \begin{bmatrix} g_{i1}^*(\boldsymbol{\theta}) \\ g_{i2}^*(\boldsymbol{\theta}) \\ \vdots \\ g_{iL}^*(\boldsymbol{\theta}) \end{bmatrix}.$$

Therefore, if individual i does not contribute to the l -th moment, then the l -th row of $\mathbf{g}_i^*(\boldsymbol{\theta})$ is filled with zero. The moment conditions that we consider are modified as:

$$E[\mathbf{g}_i^*(\boldsymbol{\theta}_0)] = \mathbf{0}.$$

The important difference from the balanced panel case is that the number of individuals who contribute to each moment can be different. Inevitably, as described below, the asymptotic distribution, the approximate distribution, and the standard errors that were presented for the balanced panel case need to be modified.

Let n_l ($\leq n$) be the number of individuals available to calculate the l -th sample moment. First, the asymptotic distribution of the GMM estimator $\hat{\boldsymbol{\theta}}$ for the unbalanced panel case depends on, instead of the above-mentioned assumption $\frac{1}{\sqrt{n}} \sum_{i=1}^n \mathbf{g}_i(\boldsymbol{\theta}_0) \rightarrow_d N(\mathbf{0}, \mathbf{S})$, the assumption that the unequally normalized sample counterpart of $E[\mathbf{g}_i^*(\boldsymbol{\theta}_0)]$ possesses an asymptotic distribution:

$$\begin{bmatrix} \frac{1}{\sqrt{n_1}} \sum_{i \in \{1\}} g_{i1}^*(\boldsymbol{\theta}_0) \\ \vdots \\ \frac{1}{\sqrt{n_L}} \sum_{i \in \{L\}} g_{iL}^*(\boldsymbol{\theta}_0) \end{bmatrix} \rightarrow_d N(\mathbf{0}, \mathbf{S}^*),$$

where $\{i \in \{l\}\}$ is the set of individuals who contribute to the l -th moment, and $\sum_{i \in \{l\}}$ denotes summation over the individuals in this set. Hence, the matrix \mathbf{S} in the asymptotic variance \mathbf{V} is replaced with the matrix \mathbf{S}^* , which is consistently estimated by the matrix $\hat{\mathbf{S}}^*$ whose (r, s) element takes the form:

$$(r, s) \text{ element of } \hat{\mathbf{S}}^* = \frac{1}{n_{rs}} \sum_{i \in \{r, s\}} g_{ir}^*(\hat{\boldsymbol{\theta}}) g_{is}^*(\hat{\boldsymbol{\theta}}),$$

where $\{i \in \{r, s\}\}$ is the set of individuals who contribute to both the r -th moment and s -th moment, and n_{rs} denotes the number of individuals in this set. Second, the matrix \mathbf{G} in the

asymptotic variance \mathbf{V} is replaced with the matrix \mathbf{G}^* , which is consistently estimated by:

$$\hat{\mathbf{G}}^* = \begin{bmatrix} \frac{1}{n_1} \sum_{i \in \{1\}} \frac{\partial g_{i1}^*(\hat{\boldsymbol{\theta}})}{\partial \boldsymbol{\theta}'} \\ \vdots \\ \frac{1}{n_L} \sum_{i \in \{L\}} \frac{\partial g_{iL}^*(\hat{\boldsymbol{\theta}})}{\partial \boldsymbol{\theta}'} \end{bmatrix}.$$

Third, and importantly, the approximate distribution for the GMM estimator is modified as:

$$\hat{\boldsymbol{\theta}} \sim N(\boldsymbol{\theta}_0, (\hat{\mathbf{G}}^{*'} \hat{\mathbf{G}}^*)^{-1} \hat{\mathbf{G}}^{*'} (\mathbf{D}^* \hat{\mathbf{S}}^* \mathbf{D}^*) \hat{\mathbf{G}}^* (\hat{\mathbf{G}}^{*'} \hat{\mathbf{G}}^*)^{-1}),$$

where $\mathbf{D}^* = \text{diag}(1/\sqrt{n_1}, \dots, 1/\sqrt{n_L})$, and:

$$\begin{aligned} (r, s) \text{ element of } \mathbf{D}^* \hat{\mathbf{S}}^* \mathbf{D}^* &= \frac{1}{\sqrt{n_r} \sqrt{n_s}} \times (r, s) \text{ element of } \hat{\mathbf{S}}^* \\ &= \frac{1}{\sqrt{n_r} \sqrt{n_s}} \times \frac{1}{n_{rs}} \sum_{i \in \{r, s\}} g_{ir}^*(\hat{\boldsymbol{\theta}}) g_{is}^*(\hat{\boldsymbol{\theta}}). \end{aligned}$$

To understand this last equation, which corresponds to equation (6.32) of MaCurdy (2007), consider again the case of balanced panels. In this case, $n = n_1 = \dots = n_L$ and $n = n_{rs}$; therefore, $\hat{\mathbf{G}}^* = \hat{\mathbf{G}}$, $\hat{\mathbf{S}}^* = \hat{\mathbf{S}}$, $1/\sqrt{n_r} \sqrt{n_s} = 1/n$, and $1/n_{rs} = 1/n$. That is, the matrix $\mathbf{D}^* \hat{\mathbf{S}}^* \mathbf{D}^*$ for the balanced panel case reduces to $\frac{1}{n} \hat{\mathbf{S}}$, so that $(\hat{\mathbf{G}}^{*'} \hat{\mathbf{G}}^*)^{-1} \hat{\mathbf{G}}^{*'} (\mathbf{D}^* \hat{\mathbf{S}}^* \mathbf{D}^*) \hat{\mathbf{G}}^* (\hat{\mathbf{G}}^{*'} \hat{\mathbf{G}}^*)^{-1} = \frac{1}{n} (\hat{\mathbf{G}}' \hat{\mathbf{G}})^{-1} \hat{\mathbf{G}}' \hat{\mathbf{S}} \hat{\mathbf{G}} (\hat{\mathbf{G}}' \hat{\mathbf{G}})^{-1}$. Thus, the matrix $\mathbf{D}^* \hat{\mathbf{S}}^* \mathbf{D}^*$ merely indicates that each element of the matrix $\hat{\mathbf{S}}^*$ is normalized by the unequal sample sizes, instead of $1/n$, when unbalanced panel data are used. Finally, the standard errors of the parameter estimates in the unbalanced panel case are calculated as the square root of the diagonal elements of $(\hat{\mathbf{G}}^{*'} \hat{\mathbf{G}}^*)^{-1} \hat{\mathbf{G}}^{*'} (\mathbf{D}^* \hat{\mathbf{S}}^* \mathbf{D}^*) \hat{\mathbf{G}}^* (\hat{\mathbf{G}}^{*'} \hat{\mathbf{G}}^*)^{-1}$.

To program the sample counterpart of $E[\mathbf{g}_i^*(\boldsymbol{\theta})]$ and the matrix $\hat{\mathbf{S}}^*$ in practice, it is convenient to use notations similar to those of Blundell et al. (2008, Appendix D). That is, conformably with the vector $\hat{\mathbf{y}}_i$, we define the $T \times 1$ vector $\mathbf{d}_i^y = (d_{i1}^y, d_{i2}^y, \dots, d_{iT}^y)'$, where d_{it}^y is 1 if \hat{y}_{it} is not missing and zero otherwise. Note that the variable d_{it}^y is related to the indicator variable introduced previously as follows: $\mathbf{D}_i \equiv \text{vech } \mathbf{d}_i^y \mathbf{d}_i^{y'} = (d_{i1}, d_{i2}, \dots, d_{iL})'$. The sample counterpart of $E[\mathbf{g}_i^*(\boldsymbol{\theta})]$ is then calculated as:

$$\text{vech} \left\{ \left(\sum_{i=1}^n \hat{\mathbf{y}}_i \hat{\mathbf{y}}_i' \right) \oslash \left(\sum_{i=1}^n \mathbf{d}_i^y \mathbf{d}_i^{y'} \right) \right\} - \text{vech} \left\{ \left(\sum_{i=1}^n \boldsymbol{\Omega}_i(\boldsymbol{\theta}) \right) \oslash \left(\sum_{i=1}^n \mathbf{d}_i^y \mathbf{d}_i^{y'} \right) \right\},$$

where \oslash denotes the element-by-element division. In the case of balanced panels, the first and second terms correspond to $\frac{1}{n} \sum_{i=1}^n \mathbf{c}_i$ and $\frac{1}{n} \sum_{i=1}^n \boldsymbol{\omega}_i(\boldsymbol{\theta})$, respectively; therefore, it turns out in this case that this equation represents $\frac{1}{n} \sum_{i=1}^n \mathbf{g}_i(\boldsymbol{\theta})$ as a whole. On the other hand, using the vector \mathbf{D}_i , the matrix $\hat{\mathbf{S}}^*$ is calculated as:

$$\hat{\mathbf{S}}^* = \left[\sum_{i=1}^n \left(\mathbf{g}_i(\hat{\boldsymbol{\theta}}) \mathbf{g}_i(\hat{\boldsymbol{\theta}})' \right) \odot (\mathbf{D}_i \mathbf{D}_i') \right] \oslash \left(\sum_{i=1}^n \mathbf{D}_i \mathbf{D}_i' \right),$$

where the symbol \odot denotes the element-by-element product.

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Table 1: Summary Statistics

Variable	1993–2004 Balanced Panel			1997–2004 Balanced Panel			1993–2004 Unbalanced Panel		
	Mean	Std.dev.	Min	Max	Mean	Std.dev.	Min	Max	Max
Panel A: All individuals									
Age	38.55	5.57	24	57	38.32	5.83	24	65	65
Annual labor earnings	592.71	209.41	119.28	3012.96	565.16	209.14	119.28	3012.96	3180.92
Annual hours worked	2417.34	475.27	728	5070	2410.91	498.13	728	5070	5096
Weekly hours worked	46.49	9.14	14	97.5	46.36	9.58	14	97.5	98
Labor market experience	18.17	6.01	1.67	39	18.14	6.17	3	50	50
Number of households		201				384			908
Number of observations		2412				3072			8162
Panel B: College-educated group									
Age	38.80	4.98	26	54	39.09	4.89	26	54	54
Annual labor earnings	686.41	223.44	129.61	3012.96	671.25	225.14	129.61	3012.96	3180.92
Annual hours worked	2351.16	426.63	728	4576	2363.02	455.06	728	4836	4836
Weekly hours worked	45.21	8.20	14	88	45.44	8.75	14	93	93
Labor market experience	16.26	5.04	3.5	31.5	16.59	4.96	3	31.5	31.5
Number of households		88				153			331
Number of observations		1056				1224			3048
Panel C: Noncollege-educated group									
Age	38.36	5.99	24	57	37.80	6.32	24	65	65
Annual labor earnings	519.74	164.27	119.28	1196.41	494.90	163.60	119.28	1196.41	1643.84
Annual hours worked	2468.88	504.14	728	5070	2442.62	522.43	728	5070	5096
Weekly hours worked	47.48	9.69	14	97.5	46.97	10.05	14	97.5	98
Labor market experience	19.66	6.29	1.67	39	19.16	6.67	3.5	50	50
Number of households		113				231			577
Number of observations		1356				1848			5114

Note: Annual labor earnings are in tens of thousands of yen and are measured in 2005 yen, adjusted using the consumer price index. Labor market experience is in years. Annual hours worked and weekly hours worked for the 1993–2004 balanced panel and the 1993–2004 unbalanced panel are based on the period 1994–2004 because there are no questionnaire items about hours worked in the 1993 survey.

Table 2: Autocovariance Matrix of Earnings Residual Calculated Using All Individuals

Year	1993–2004 Balanced Panel				1997–2004 Balanced Panel				1993–2004 Unbalanced Panel			
	Autocovariances				Autocovariances				Autocovariances			
	$\text{Var}(\hat{y}_{it})$ (1)	$(\hat{y}_{it}, \hat{y}_{it+1})$ (2)	$(\hat{y}_{it}, \hat{y}_{it+2})$ (3)	$(\hat{y}_{it}, \hat{y}_{it+3})$ (4)	$\text{Var}(\hat{y}_{it})$ (5)	$(\hat{y}_{it}, \hat{y}_{it+1})$ (6)	$(\hat{y}_{it}, \hat{y}_{it+2})$ (7)	$(\hat{y}_{it}, \hat{y}_{it+3})$ (8)	$\text{Var}(\hat{y}_{it})$ (9)	$(\hat{y}_{it}, \hat{y}_{it+1})$ (10)	$(\hat{y}_{it}, \hat{y}_{it+2})$ (11)	$(\hat{y}_{it}, \hat{y}_{it+3})$ (12)
1993	0.0882 (0.0095)	0.0727 (0.0098)	0.0688 (0.0082)	0.0720 (0.0088)	—	—	—	—	0.1171 (0.0085)	0.0913 (0.0070)	0.0910 (0.0067)	0.0906 (0.0069)
1994	0.0868 (0.0119)	0.0726 (0.0089)	0.0735 (0.0103)	0.0738 (0.0103)	—	—	—	—	0.1095 (0.0089)	0.0925 (0.0071)	0.0916 (0.0072)	0.0921 (0.0078)
1995	0.0803 (0.0084)	0.0741 (0.0085)	0.0736 (0.0088)	0.0715 (0.0082)	—	—	—	—	0.1154 (0.0078)	0.0972 (0.0067)	0.0950 (0.0066)	0.0936 (0.0067)
1996	0.0916 (0.0102)	0.0841 (0.0101)	0.0804 (0.0094)	0.0819 (0.0096)	—	—	—	—	0.1120 (0.0073)	0.1008 (0.0068)	0.0990 (0.0067)	0.0958 (0.0069)
1997	0.0994 (0.0120)	0.0845 (0.0105)	0.0887 (0.0107)	0.0851 (0.0104)	0.1026 (0.0079)	0.0879 (0.0073)	0.0858 (0.0070)	0.0841 (0.0070)	0.1129 (0.0064)	0.0977 (0.0058)	0.0931 (0.0058)	0.0906 (0.0058)
1998	0.0972 (0.0112)	0.0902 (0.0107)	0.0894 (0.0101)	0.0914 (0.0106)	0.1082 (0.0085)	0.0917 (0.0075)	0.0919 (0.0074)	0.0932 (0.0077)	0.1172 (0.0066)	0.1048 (0.0063)	0.1004 (0.0062)	0.0984 (0.0061)
1999	0.1018 (0.0111)	0.0975 (0.0113)	0.1009 (0.0115)	0.0963 (0.0110)	0.1024 (0.0077)	0.0927 (0.0072)	0.0959 (0.0076)	0.0919 (0.0073)	0.1348 (0.0077)	0.1137 (0.0071)	0.1125 (0.0071)	0.1113 (0.0075)
2000	0.1107 (0.0129)	0.1095 (0.0130)	0.1053 (0.0128)	0.1056 (0.0133)	0.1090 (0.0085)	0.1034 (0.0084)	0.0988 (0.0081)	0.1017 (0.0085)	0.1310 (0.0077)	0.1175 (0.0074)	0.1136 (0.0072)	0.1106 (0.0075)
2001	0.1220 (0.0137)	0.1147 (0.0136)	0.1157 (0.0143)	0.1104 (0.0148)	0.1221 (0.0092)	0.1105 (0.0086)	0.1136 (0.0092)	0.1092 (0.0095)	0.1402 (0.0079)	0.1245 (0.0075)	0.1219 (0.0077)	0.1176 (0.0084)
2002	0.1229 (0.0146)	0.1183 (0.0145)	0.1142 (0.0153)	—	0.1178 (0.0090)	0.1153 (0.0093)	0.1124 (0.0098)	—	0.1480 (0.0091)	0.1367 (0.0080)	0.1297 (0.0088)	—
2003	0.1473 (0.0207)	0.1329 (0.0173)	—	—	0.1397 (0.0123)	0.1255 (0.0109)	—	—	0.1669 (0.0111)	0.1464 (0.0098)	—	—
2004	0.1552 (0.0213)	—	—	—	0.1425 (0.0129)	—	—	—	0.1652 (0.0103)	—	—	—

Note: Standard errors are in parentheses. Variance and autocovariances are cross-sectional ones. Three columns labeled Autocovariances in each panel report $\text{Cov}(\hat{y}_{it}, \hat{y}_{it+1})$, $\text{Cov}(\hat{y}_{it}, \hat{y}_{it+2})$, and $\text{Cov}(\hat{y}_{it}, \hat{y}_{it+3})$, respectively.

Table 3: Estimates of the Profile Heterogeneity and Restricted Models Using All Individuals (Balanced Panel)

Parameter	Model							
	Panel A: Profile Heterogeneity				Panel B: Restricted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ρ	0.595 (0.348)	0.384 (0.157)	0.629 (0.284)	0.331 (0.136)	1.049 (0.057)	1.026 (0.043)	1.012 (0.059)	0.922 (0.039)
$\sigma_\beta^2 \times 100$	0.033 (0.012)	0.044 (0.012)	0.057 (0.020)	0.076 (0.022)	—	—	—	—
$\sigma_{\alpha\beta} \times 100$	-0.339 (0.174)	-0.525 (0.191)	-0.764 (0.296)	-1.093 (0.369)	—	—	—	—
σ_α^2	0.090 (0.029)	0.120 (0.032)	0.164 (0.044)	0.217 (0.060)	0.066 (0.009)	0.064 (0.009)	0.080 (0.007)	0.077 (0.007)
σ_η^2	0.011 (0.008)	0.016 (0.002)	0.010 (0.004)	0.017 (0.001)	0.003 (0.002)	0.004 (0.002)	0.005 (0.002)	0.011 (0.002)
σ_ϵ^2								
1993	0.012 (0.010)	—	—	—	0.019 (0.005)	—	—	—
1994	0.005 (0.007)	—	—	—	0.015 (0.006)	—	—	—
1995	-0.005 (0.008)	—	—	—	0.004 (0.005)	—	—	—
1996	0.002 (0.009)	—	—	—	0.012 (0.006)	—	—	—
1997	0.006 (0.011)	—	0.012 (0.005)	—	0.015 (0.006)	—	0.018 (0.004)	—
1998	-0.000 (0.011)	—	0.012 (0.006)	—	0.008 (0.006)	—	0.018 (0.005)	—
1999	-0.001 (0.009)	—	0.001 (0.005)	—	0.008 (0.004)	—	0.006 (0.004)	—
2000	0.002 (0.008)	—	0.003 (0.006)	—	0.011 (0.007)	—	0.007 (0.004)	—
2001	0.007 (0.008)	—	0.011 (0.005)	—	0.016 (0.006)	—	0.014 (0.004)	—
2002	0.001 (0.008)	—	-0.000 (0.005)	—	0.010 (0.007)	—	0.004 (0.004)	—
2003	0.018 (0.013)	—	0.014 (0.006)	—	0.027 (0.013)	—	0.020 (0.007)	—
2004	0.017 (0.014)	—	0.008 (0.008)	—	0.026 (0.014)	—	0.016 (0.007)	—
Panel used	93–04	93–04	97–04	97–04	93–04	93–04	97–04	97–04
#households	201	201	384	384	201	201	384	384
#observations	2412	2412	3072	3072	2412	2412	3072	3072

Note: Standard errors are in parentheses. 93–04 and 97–04 in the third row from the bottom (Panel used) denote that the 1993–2004 balanced panel and the 1997–2004 balanced panel are used for estimation, respectively.

Table 4: Estimates of the Profile Heterogeneity and Restricted Models by Education Group (Balanced Panel)

Parameter	Model							
	Panel A: Profile Heterogeneity				Panel B: Restricted			
	College (1)	Noncollege (2)	College (3)	Noncollege (4)	College (5)	Noncollege (6)	College (7)	Noncollege (8)
ρ	0.286 (0.818)	0.804 (0.188)	0.493 (0.668)	0.896 (0.203)	1.168 (0.119)	0.930 (0.057)	1.114 (0.093)	0.857 (0.072)
$\sigma_{\beta}^2 \times 100$	0.030 (0.011)	0.020 (0.018)	0.059 (0.026)	0.020 (0.074)	—	—	—	—
$\sigma_{\alpha\beta} \times 100$	-0.343 (0.153)	-0.262 (0.252)	-0.693 (0.349)	-0.414 (1.066)	—	—	—	—
σ_{α}^2	0.080 (0.023)	0.080 (0.040)	0.121 (0.047)	0.134 (0.127)	0.044 (0.010)	0.048 (0.008)	0.052 (0.008)	0.056 (0.007)
σ_{η}^2	0.012 (0.035)	0.011 (0.004)	0.007 (0.008)	0.010 (0.002)	0.000 (0.001)	0.008 (0.003)	0.002 (0.002)	0.012 (0.004)
σ_{ϵ}^2								
1993	0.000 (0.034)	0.022 (0.008)	—	—	0.013 (0.008)	0.027 (0.008)	—	—
1994	0.015 (0.027)	-0.002 (0.004)	—	—	0.028 (0.009)	0.003 (0.007)	—	—
1995	-0.005 (0.037)	-0.009 (0.006)	—	—	0.007 (0.007)	-0.005 (0.008)	—	—
1996	0.003 (0.034)	0.001 (0.007)	—	—	0.016 (0.006)	0.004 (0.006)	—	—
1997	-0.003 (0.036)	0.007 (0.009)	0.008 (0.009)	0.011 (0.004)	0.011 (0.005)	0.009 (0.008)	0.012 (0.005)	0.014 (0.006)
1998	0.010 (0.040)	-0.000 (0.009)	0.015 (0.012)	0.015 (0.005)	0.024 (0.012)	0.001 (0.008)	0.020 (0.008)	0.014 (0.006)
1999	-0.005 (0.037)	0.001 (0.006)	0.008 (0.009)	0.002 (0.004)	0.009 (0.005)	0.002 (0.005)	0.013 (0.005)	0.000 (0.005)
2000	-0.002 (0.035)	0.006 (0.007)	0.004 (0.008)	0.004 (0.005)	0.012 (0.005)	0.007 (0.008)	0.009 (0.004)	0.002 (0.005)
2001	-0.007 (0.035)	0.019 (0.007)	0.008 (0.010)	0.012 (0.004)	0.006 (0.005)	0.021 (0.007)	0.013 (0.007)	0.010 (0.005)
2002	-0.012 (0.033)	0.006 (0.008)	-0.003 (0.008)	0.002 (0.005)	-0.000 (0.006)	0.010 (0.009)	0.001 (0.004)	0.000 (0.005)
2003	-0.005 (0.031)	0.030 (0.018)	0.001 (0.008)	0.023 (0.008)	0.004 (0.006)	0.035 (0.020)	0.005 (0.004)	0.022 (0.010)
2004	0.040 (0.032)	0.004 (0.010)	0.021 (0.015)	0.005 (0.006)	0.042 (0.026)	0.013 (0.012)	0.024 (0.014)	0.005 (0.006)
Panel used	93–04	93–04	97–04	97–04	93–04	93–04	97–04	97–04
#households	88	113	153	231	88	113	153	231
#observations	1056	1356	1224	1848	1056	1356	1224	1848

Note: Standard errors are in parentheses. 93–04 and 97–04 in the third row from the bottom (Panel used) denote that the 1993–2004 balanced panel and the 1997–2004 balanced panel are used for estimation, respectively.

**Table 5: Estimates of the Profile Heterogeneity and Restricted Models
(Unbalanced Panel)**

Parameter	Model							
	Panel A: Profile Heterogeneity				Panel B: Restricted			
	All (1)	All (2)	College (3)	Noncollege (4)	All (5)	All (6)	College (7)	Noncollege (8)
ρ	0.688 (0.167)	0.470 (0.077)	0.856 (0.144)	0.604 (0.259)	0.900 (0.016)	0.860 (0.013)	0.904 (0.028)	0.873 (0.024)
$\sigma_\beta^2 \times 100$	0.035 (0.005)	0.034 (0.004)	0.032 (0.018)	0.028 (0.005)	—	—	—	—
$\sigma_{\alpha\beta} \times 100$	-0.167 (0.047)	-0.140 (0.058)	-0.232 (0.100)	-0.166 (0.051)	—	—	—	—
σ_α^2	0.030 (0.008)	0.026 (0.009)	0.039 (0.013)	0.024 (0.009)	0.032 (0.003)	0.031 (0.003)	0.022 (0.004)	0.022 (0.003)
σ_η^2	0.010 (0.002)	0.020 (0.002)	0.006 (0.003)	0.009 (0.004)	0.013 (0.001)	0.020 (0.001)	0.011 (0.002)	0.012 (0.002)
σ_ϵ^2								
1993	0.018 (0.004)	—	0.012 (0.003)	0.019 (0.006)	0.028 (0.004)	—	0.012 (0.004)	0.029 (0.005)
1994	0.006 (0.004)	—	0.013 (0.005)	0.003 (0.006)	0.011 (0.004)	—	0.017 (0.006)	0.008 (0.005)
1995	0.008 (0.005)	—	0.005 (0.004)	0.006 (0.006)	0.012 (0.003)	—	0.007 (0.002)	0.009 (0.004)
1996	0.005 (0.004)	—	0.006 (0.004)	0.005 (0.006)	0.008 (0.003)	—	0.006 (0.004)	0.009 (0.003)
1997	0.013 (0.004)	—	0.012 (0.004)	0.009 (0.006)	0.017 (0.003)	—	0.012 (0.006)	0.012 (0.003)
1998	0.012 (0.005)	—	0.023 (0.006)	0.007 (0.006)	0.018 (0.003)	—	0.022 (0.007)	0.012 (0.004)
1999	0.024 (0.005)	—	0.017 (0.006)	0.023 (0.007)	0.031 (0.005)	—	0.017 (0.006)	0.030 (0.006)
2000	0.012 (0.006)	—	0.015 (0.007)	0.011 (0.006)	0.020 (0.004)	—	0.016 (0.006)	0.019 (0.005)
2001	0.010 (0.005)	—	0.009 (0.007)	0.014 (0.006)	0.020 (0.004)	—	0.012 (0.006)	0.024 (0.005)
2002	0.008 (0.005)	—	0.002 (0.007)	0.011 (0.006)	0.023 (0.005)	—	0.009 (0.006)	0.025 (0.006)
2003	0.011 (0.005)	—	0.003 (0.006)	0.015 (0.006)	0.026 (0.006)	—	0.012 (0.008)	0.030 (0.007)
2004	0.000 (0.004)	—	0.012 (0.010)	-0.002 (0.005)	0.018 (0.005)	—	0.025 (0.011)	0.015 (0.005)
#households	908	908	331	577	908	908	331	577
#observations	8162	8162	3048	5114	8162	8162	3048	5114

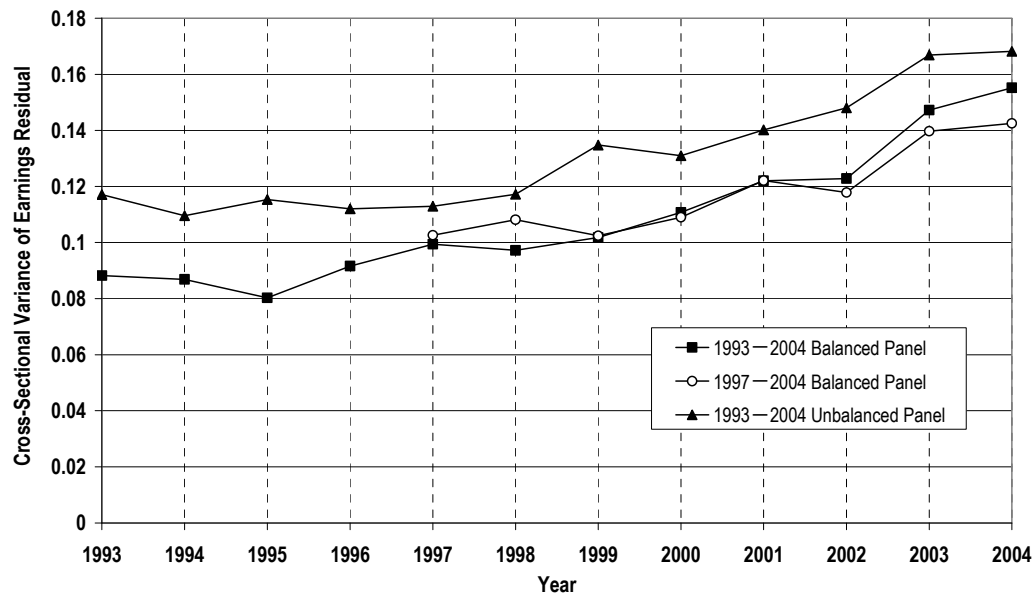
Note: Standard errors are in parentheses.

Table 6: Estimates of the Profile Heterogeneity Model Based on Alternative Grouping and Specification (Unbalanced Panel)

Parameter	Profile Heterogeneity Model						
	Panel A		Panel B				
	Without non-high school graduates		With occupation dummy variables				
	High school	All	All	All	College	Noncollege	High school
	(1)	(new)	(original)	(new)	(5)	(6)	(7)
ρ	0.697	0.749	0.780	0.806	0.847	0.722	0.764
	(0.183)	(0.128)	(0.078)	(0.065)	(0.121)	(0.149)	(0.115)
$\sigma_{\beta}^2 \times 100$	0.025	0.030	0.019	0.015	0.022	0.019	0.014
	(0.006)	(0.007)	(0.006)	(0.007)	(0.013)	(0.005)	(0.006)
$\sigma_{\alpha\beta} \times 100$	-0.114	-0.116	-0.155	-0.120	-0.237	-0.129	-0.077
	(0.056)	(0.049)	(0.044)	(0.049)	(0.078)	(0.046)	(0.052)
σ_{α}^2	0.014	0.022	0.032	0.029	0.042	0.024	0.016
	(0.010)	(0.009)	(0.008)	(0.009)	(0.012)	(0.009)	(0.011)
σ_{η}^2	0.009	0.010	0.011	0.012	0.007	0.010	0.011
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
σ_{ϵ}^2							
1993	0.019	0.019	0.019	0.018	0.011	0.021	0.019
	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
1994	0.004	0.007	0.008	0.008	0.012	0.004	0.005
	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
1995	0.009	0.010	0.011	0.012	0.008	0.009	0.010
	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.006)
1996	0.008	0.006	0.005	0.006	0.007	0.006	0.008
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
1997	0.011	0.015	0.019	0.019	0.017	0.014	0.014
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
1998	0.005	0.012	0.015	0.013	0.022	0.010	0.007
	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)
1999	0.021	0.022	0.026	0.024	0.018	0.026	0.024
	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)
2000	0.013	0.014	0.019	0.020	0.010	0.018	0.019
	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
2001	0.011	0.009	0.015	0.015	0.010	0.017	0.015
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
2002	0.014	0.010	0.015	0.017	0.010	0.014	0.016
	(0.007)	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)
2003	0.015	0.009	0.016	0.016	0.012	0.018	0.018
	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
2004	-0.003	0.001	0.009	0.008	0.014	0.004	0.003
	(0.005)	(0.005)	(0.004)	(0.005)	(0.009)	(0.005)	(0.005)
#households	493	824	908	824	331	577	493
#observations	4382	7430	8162	7430	3048	5114	4382

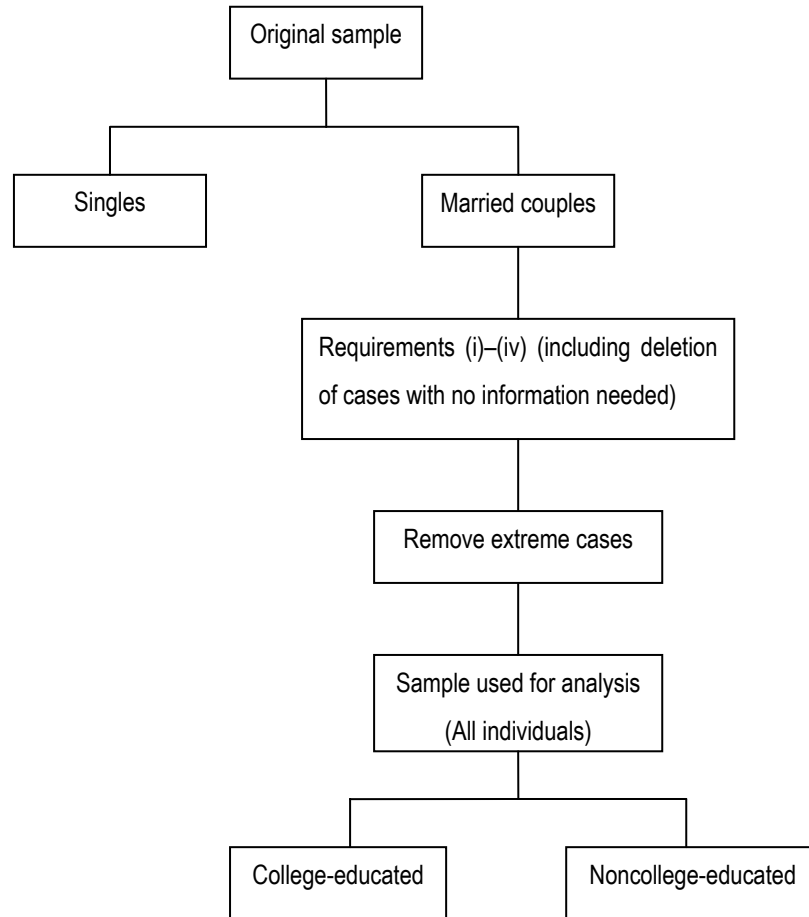
Note: Standard errors are in parentheses. All (original) denotes the original sample composed of the college-educated group and the noncollege-educated group, and All (new) denotes the sample excluding non-high school graduates from the original one.

Figure 1: Cross-Sectional Variance of Earnings Residual, 1993–2004



Note: Data for this figure are from columns (1), (5), and (9) of Table 2.

Appendix Figure 1: Derivation of Sample



Note: The samples used for analysis are selected from the original sample using the following criteria. (i) The respondent and her spouse are a continuously married couple. Further, the spouse (i.e., husband of the respondent) (ii) is classified as an employee using the definition of the JPSC, (iii) reports positive labor earnings, and (iv) reports annual hours of work between 728 and 5096 hours. After this selection, some cases with extreme values of real earnings (a growth rate above 250 percent or below 80 percent, or a level below one billion yen) are removed. The college-educated group consists of individuals with a four-year college degree, and the noncollege-educated group consists of individuals without a four-year college degree.